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Integrating Intelligent Chip Design with Agentic AI: Building the Future of Smart Wireless Communication Systems

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Abstract

Recent breakthroughs in Artificial Intelligence (AI) are propelling society towards a new technological era, wherein intelligent systems can independently observe and interpret their environment, make optimal decisions, and act accordingly. Agentic AI is evolving from tool AI to an entity that operates without human involvement. Almost all aspects of society are now being impacted by this rapid proliferation of Agentic AI, such as the public sector, education, finance, healthcare, entertainment, media, and automotive. In parallel, composite intelligent chip design, encompassing chip architecture, chip implementation and chip manufacturing, is urgently needed amid soaring demand for computation and communication. Despite initial optimism about Moore's law, the efficacy of silicon-based chips has seen degradation. One potential route for intelligent chip design is inspired by biological exploration, which could involve the evolution of chips along a co-developed path guided by environmental pressure. Chip designs with complex functionalities require optimization strategies that surpass the capabilities of current silicon-based chips.

The realization of such a vision could result in completely new architectures using advanced materials and manufacturing techniques, as well as translating these designs into novel chip automatons. However, this path would involve fundamental breakthroughs over decades and would render legacy chips obsolete. A complementary route for rapid maturity involves applying agentic AI to intelligent chip design, resulting in new AI-native chips. These chips would come integrated with learned weights from training AI models, providing immediate acceleration to on-chip inference. In addition, agentic AI could dramatically speed up the training and design of intelligent chips for next-gen wireless systems. AI tools could be utilized to provide domain knowledge on chip design, chip operation, and workflow optimization.

Agentic AI ridden with new challenges for regulation and safety concerns leads to the notion of regulatory compliance, which encompasses social norms, laws, regulations and standards. Such a deep embedding of regulatory compliance in agentic systems could enable compliance by design, imbuing them with performance enhancing abilities. Furthermore, any codes, tools and metrics devised by humans for regulation on agentic systems could be adopted as learning signal to pursue optimal policies for compliance, thus inheriting pre-existing processes. Looking ahead, the rapid proliferation of agentic AI is poised to alter the course of the next wireless communications revolution.

Keywords: Intelligent Chip Design, Agentic AI, Smart Wireless Communication, Edge Computing, AI Hardware Integration, 6G Networks, Autonomous Systems, Low-Latency Processing, Neural Accelerators, Embedded AI, Real-Time Data Processing, Energy-Efficient Chips, Cognitive Radio, AI-Driven Signal Processing, Intelligent Transceivers

1. Introduction

The extraordinary rise in radio-frequency (RF) electromagnetic waves being used for wireless communication has come with tremendous societal and economic benefits. However, complexities in the fundamental physics of RF waves, noise, uncertainty, and the impoverished network infrastructure being rapidly built are continuing to plague the performance of wireless communication systems. Action plans and solutions are still being contemplated and implemented in academia and industry. Continuing to optimize wireless systems using heuristic methods, without a proper mathematical framework, akin to weeks of tantalizing success in trying to hold a sneeze while being infected by one of the many funerally humming viruses circulating in contemporary society, is neither effective nor sustainable [1]. An urgent paradigm shift in both wireless theory and technology is paramount. This text argues that this shift into the third wave of wireless communication evolution could be launched by a disruptive price point and characteristic architecture stemming from insights and principles grounded in mathematical theory. The aim is to develop an in-depth understanding of design principles, insights, and pathways towards launching such capability-decoupled systems with extreme speed are expounded.

Three fundamental characteristics that would fundamentally differentiate future 6G from the current wave of wireless ecosystems are envisioned. Currently, wireless systems are broadly tuned, capable of operating under a wide band of frequencies, but not all of them are used at the same time. Each access point mediates the rationing of band utilization by connecting vehicles on the fly to the cloud. This architecture is a human-centric bottom-up by-product of a market economy. Conversely, tailored systems are envisioned that involve resolved bands, centroids, thresholds, and ranges directly linked to the transmitter-receiver pairs. Such systems may have the capability of a multi-order, multi-resolved, and exponentially cascading fiber length for tuning the communication medium after probing and in some instances even aided by active medium choice. The theories of such chaotic, sprouting, ability-decoupled systems are not yet far advanced. New venues in controlling the degrees of freedoms of the canonical governing equation need to be explored. Chipped waves for high-fidelity wave propagation and time-reversed synthetic waves mimicking said waves for accurate estimation are potentially two candidates.

2. Background and Motivation

A key feature of the success of communication technology over the past century has been the design of cost-effective and compact intelligent chips that efficiently realize the functions specified by the underlying theory. Terrestrial communication systems, both general-purpose wireless and dedicated or point-to-point wired, have benefited greatly from the rapid evolution of chip technology over the past few decades. It is curious why this aspect of chip technology has not yet been sufficiently explored in the recent intense investigation of future synthetic agents. With more than half a century of experience behind them, there are compelling technical motivations to ask how well the state-of-the-art chip technology can be integrated with the agentic artificial intelligence that is beginning to emerge. If so, what are the implications for the development of such agentic AI? And if not, what are the limitations of the general-purpose chip technology in this ambitious development of artificial general intelligence? These are some fundamental questions that need to be addressed.

To be more specific, can the current rational or even irrationally intelligent general-purpose chip technology to run the emerging agentic AI? If this task is possible, what are the basic architectures of the hybrid intelligent chip, its topological structure, and the thermodynamic implications for data transmission and information processing? How are various neural circuits dynamically regulated at multi-scales, and the generative models that play a central role in logical reasoning and practical generation trained in a self-supervised manner? Or, if this task is impossible, what are the fundamental bottlenecks of the existing conventional circuit technology? Will AGI with the same or superior capabilities as human beings be possible at all? Will AGI robustly emerge or gradually develop? And what are the implications of such AGI for the existence of humankind?

To address these questions, a unified membrane computing framework for both intelligent agent and chip technology is developed for the first time. This framework provides a structured paradigmatic language within which agentic intelligence, whether biological or man-made, can be expressed. From this perspective, AGI can be viewed as a clarification of the long-term theories of intelligence. It is revealed that the current AI technology, including the cutting-edge generative neural networks, cannot fulfill the key functional requirements for agentic intelligence, but should more properly be categorized as a kind of artificial narrow intelligence. Unlike existing neural network-based technologies designed heuristically, the egg-memory architecture of the intelligent chip in the described communication technology integrates information transmission, processing, and storage functions in a similar fashion as primary intelligence, and thus provides a plausible, effective hardware foundation for developing agentic intelligence at the level of AGI or above. Moreover, it is shown that not only the analogue switch, but all digital switch technologies, no matter how sophisticated they are, inevitably fall short of constructing robustly agentic intelligence.

3. Overview of Intelligent Chip Design

The goal of enabling AI-capable machines with perception, decision-making, abstraction, planning, and adaptation abilities requires the miniaturization of these elements to the chip level. Past advances in AI have largely focused on data-mining and robotic approach, while masking of intelligence and focusing on raw computation has been dismissed. However, such approaches are relatively easier to translate to digital systems. Building autonomous AGI machines even with existing low power AI chips would require complex interface electronics, high computing capacity, and infrastructure. Additionally, the primary concerns would revolve around energy efficiency, real-time response times (microseconds to milliseconds timelines), fast decision-making skills (from simple fight-or-flight to complex high-level imaginary planning), agility, and many others. Agility includes the ability to effectively learn from experience and adapt it to novel scenarios, and applying it to overall system-level designs including chips and networks.

An increasing number of such functions are being built with biomimicry and sensing control circuits. The energy-

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efficient AI chips built by mimicking neural networks (NNs) or brain architectures have shown promising results. More advanced neural network architectures such as event-based and spiking NNs have also been demonstrated to have significant energy efficiency advantages. Generally, looking at the AI chip market today, many of the chips are good at solving weak-AI problems at much lower energy and on-chip area compared to their server-based alternatives. Since this processing is done within the edge devices, the response times and link reliability improve significantly, making them closer to suitable for real-time use.

However, while these show early industrial- and market-level impacts, they largely do not address the issue of general intelligence in hardware. The nature of general intelligence includes but is not limited to modalities corresponding to sight, sound, issology, body movement, mobility, abstraction, and planning intelligence with elements from very different fields functioning in coherent and coordinated ways to achieve complex hierarchical goals and purposes [2]. With this understanding of general intelligence and observation of existing weak intelligence chipping systems, three primary AI chip actions can be proposed: modeling representation, enabling rapid inference, and menu-driven execution [3].

3.1. Fundamental Principles

Conventional techniques that have provided many benefits to wireless communication systems nonetheless have fundamental limitations. A radical design philosophy that forgoes prior assumptions and architectures, and takes as an inspiration the biological basis of intelligence may yield a communication paradigm order of magnitude more capable than previous generations [1]. Biological organisms efficiently communicate in a diverse array of extremely dynamic environments, often with minimal or no prior assumptions on the likelihood of signals and/or channel realizations. These variants of non-stationarity are often viewed as impediments to efficient communications in conventional communication systems. In contrast, AGI-native systems proactively harness these uncertainties to relieve themselves of assumptions they cannot or have not specified.

The starting point is the observation that intelligence arises from the interaction of agents and the surfaces of interactions with which they couple. The a priori specification of underlying structures often presumed in conventional systems results in brittle naïve architectures that degrade when they inevitably encounter unmodeled structures. Communications in such interactions rely on a wide range of spatial and temporal scales, and thus must necessarily resort to hybrid structures that escape descriptive models. The lack of agentic behavior in conventional systems is the source of the brittleness that limits their power [2]. Consequently, a new integration of AGI hardware to accompany the traditional co-design of AGI communication systems and chips is envisioned.

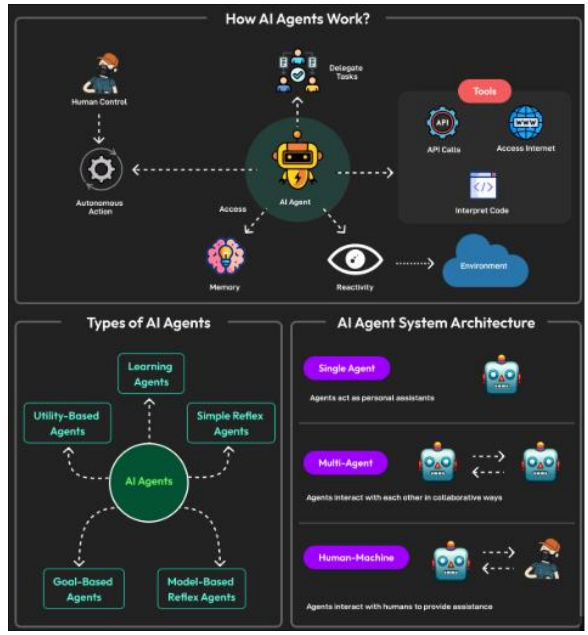

Fig 1: An AI Agent

3.2. Recent Advances

Recent developments in chip fabricating technologies, such as Moore's Law, that leads to the significant increase of CMOS scaling, promote the construction of high-performance combat agents. Such agent designs or operations are discussed in the previously published articles [4]. In addition, a new design methodology which combines knowledge-based intelligent chip design with agentic artificial intelligence is proposed. Such "intelligent" chips apply agentic AI algorithms to achieve adversarial strategy learning, real-time electromagnetic intelligence matching and multi-agent online cooperative playing, without precise mathematical models or algorithms. Integrating such "intelligent" chips with "agentic AI" breaks through the efficiency bottleneck of massive training computations, enabling the practical application of agentic AI in both millimeter-wave and terahertz communications.

Recently, new agentic AI-based combat protocols, such as OMMA/NOMA, are proposed, which significantly improve wireless communication performance. Such protocols bring a challenge to the chip designers, which require a large computation parallelization and multicasting capability. Recent silicon-containing technologies can speed up the

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switching rate to hundreds of THz, where an advanced chip design methodology is required to precisely predict agents' strategy convergence and quantization performance. Because of the great advance in chip design technologies, intelligent chips which have built-in knowledge-based intelligent computing units and commercially available learning algorithms are becoming mature. Such "intelligent" chips based on hybrid AI thermodynamics achieve significant industrial deployment automatically. Such intelligent chips are used as auxiliary components to prototype the combat agents, enabling complex chip design.

Eqn.1:Shannon-Hartley Theorem (Wireless Communication Capacity)

$$C = B \cdot \log_2\left(1 + \frac{S}{N}\right)$$

- **C**: Channel capacity (bps)
- **B**: Bandwidth (Hz)
- **S/N**: Signal-to-noise ratio

In addition, cutting the gap between prior knowledge-based chip design and agentic AI algorithms which have increasing market demand is also needed. On one side, knowledge-based intelligent chip designs are abundant in infrastructure. Given a comprehensive agentic AI-based combat protocols designing methodology, such intelligent chips can match the popular AI protocols by chip design engineer. On the other side, existing knowledge-based algorithms are often complicated and require precise mathematical models, which can only optimise designs in test cases with small dimension and thus have limited application.

3.3. Challenges in Design

As functionalities have increased in microsystems, the search is on for the "perfect" device that is stable, reliable, easy to fabricate, and has a simple function. Hardware models for implementing intelligence are often used to design high-performance chips for edge computing. Unfortunately, not all designed devices work as intended, and the development process is lengthy and costly. The advent of ultra-scaled devices and new fabrication technologies has opened up the field of quantum devices and computing, which allows for novel techniques in the area of neural chip designs [2]. In general, the rigidity in design and innovation is much higher when designing standard cells for digital and analog circuits. For devices which produce outputs based on differential measurements, the variation in performance as determined by extrinsic influences is higher, including parasitics and wearing of the device. The impact of performance errors in standard cells for analog devices is compounded in the neural chips which rely on mixing analog and digital devices, or hybrid chips that use VLSI circuitry programming in FPAA-like fabrics. Specifically, designers of neural circuits need to recognize the device-level issues which may be plaguing the performance of their chips.

An overview of the commonly used standard cells to build basic neural circuit blocks such as dot-product computation and activation functions will be covered. Efficient designs of memory and state transitions, which are often overlooked in studies on neuromorphic devices, will be included at the RTL-level. Agnostic to the technology used, the large design space and diversity of function means many neural circuit blocks are needed to build chip/system blocks for AGI chips aimed at general intelligence applications. As efforts in realization of AGI chips intensify, there is a growing call for research visions and roadmaps specifically tailored for the development of such chips. The aim of AGI chips is nothing short of matching the spectrum of human intelligence, of which machine learning is a small subset, and thus allowing for innovation and generalization of utility beyond what is task trained. This presents challenges for chip developers, who need to 1.) provide the scalability to train on and store a multitude of parameters; and 2.) the latency to access said weights and inputs for accurate and instantaneous inference. Automating the chip design flow is crucial to speed-up the scarce resource intensive process and reduce costs for AGI chip development. While there exist many tools for automating the full ASIC design flow in the well understood digital chip market, the same cannot be said for the analog market where design automation is often more challenging than with digital due to many domain specific issues, like matching device parasitics and thermal effects.

4. Understanding Agentic AI

A general agent with a high level of artificial intelligence is generally referred to as Artificial General Intelligence (AGI), which is colloquially known as "strong" AI, "full" AI, "human-level" AI, or "superintelligence." Artificial Agents possess human-like capabilities and intelligence and possess human-like cognitive functions, such as common sense reasoning. The path to Artificial General Intelligence (AGI) chip development is foreshadowed by hardware development in other fields, such as general-purpose computation and graphics processing. The physical limitations of transistor size will drive the next technologies to mass adoption, requiring a hardware development boom

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for AGI machines. Building a mass-wide adoption AGI machine would require a plethora of complex interface electronics, which communicate with multiple component technologies. These components would each require the necessary infrastructure to support their operation. The three agentic facets of intelligent chips and their technological implications are discussed [2]. The understanding of agentic AI is drawn upon.

Wireless systems, like any systems, will initially be AGI-less. However, manually building AGI-less networks will impose immense challenges. Thus, the primary challenge is how to bootstrap wireless networks' ability to manufacture an initial world model. The term world model is used in the context that wireless networks have the physical domain that governs their behavior. The physical domain is a large subdomain of the causal universe. Wireless networks will need to start with a world model from a small physical domain [1].

By design, tiny wireless networks using developmentally-inspired bootstraps can learn world models of large physical domains. Developmentally-inspired bootstraps are notions inspired by evolutionary developmental biology and are broadly defined as a series of iterations of actions and reactions of an initially agent-less system that create higher-level functions and agents. More specifically, while systemic contextual representations are generally agent-less, representations at lower levels need to be agent-less. These bootstraps can create the capability of wireless networks to manufacture common sense and an initial, small set of self-supervised agents. Once this is done, simpler concepts can emerge endogenously, and agentic behavior will naturally, rapidly, and robustly evolve by complex social interaction. A first-generation class of networked AGI systems using a novel brain architecture is illustrated. A variety of networks across many fields will have an initial burst of rapid research.

Fig 2: The AI Agent Revolution

4.1. Definition and Characteristics

The rapid growth in artificial intelligence (AI) applications and acceptance in everyday life has been enormous since the introduction of ChatGPT and StableDiffusion in the Autumn of 2022. As a consequence, a plethora of AI applications are being discovered daily that attract masses of people. A sudden interest in AI-hardware and AI-chips is evident. AI-chips with embedded learning algorithms will likely proliferation in edge devices, in integrated circuits (ICs), systems-on-chip (SoCs), and systems-in-packages (SiPs) alike. AI-chips are most popular in telecommunication devices and applications. Almost all leading edge-device manufacturers are investing heavily in developing AI-based data treatment functions and embedded AI-chips for their devices. The planned devices include the latest generation of automobiles, security and monitoring cameras, drones, and other infrastructure devices of smart cities. They all contribute to data collection, curation, and treatment for feeding the ever-increasing demand for a data-driven intelligent digital twin model of Earth. A paradigm shift will occur, from a WiFi-based Internet of Things (IoT) higher on Moore's Law and von Neumann architecture to AI-biochip rather an Internet of Intelligence (IoI) lower on power efficiency and non-von Neumann architecture.

In AI-native systems, AI becomes a central component for deploying, optimizing, and operating communication networks throughout their lifecycle. AI-native systems can learn and improve their performance by exploiting advanced learning techniques that enable wireless networks to gain system knowledge and expand it into different scenarios. The wireless industry has witnessed a remarkable increase in the types of wireless devices and applications that have begun using AI tools. As a result of this, the demand for bigger and more intense AI solutions has increased, requiring more powerful data centers and chips, more networking devices and bandwidth, and more energy-intensive computation and storage. The most pressing issues currently affecting this ecosystem's development are the flaws in its performance such as broken Dead Weiss, Cloudwalls, and most importantly that the human limit to absorb and understand wireless models in principle limits the complexity of the models that can be evaluated. Since those models define the performance of the wireless systems and their accuracy determines the level of performance they can achieve, it can be said that none of the possible models that can be obtained under those hypotheses will be able to reach the performance needed by the whole cellular systems in future generations [1].

The wireless industry has witnessed a remarkable increase in the types of wireless devices and applications that have begun using AI tools. As a result of this, the demand for

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4.2. Applications in Communication

Next generation wireless communication systems must evolve further to cope with an even larger paradigm shift toward the ultra-dense deployment of devices and systems. Proposed applications of new systems demand ultra-high data rate, massive data processing, smart designs, low-cost deployment, reliability, and security, all in a dynamic environment. Addressing these challenges requires a paradigm shift in the design of wireless communication systems and networks. In addition to the ongoing optimization of signal processing and engineering on the physical layer, a more holistic integration across multiscale hierarchical architectures with new intelligent features at varied levels is vital to meet the highly heterogeneous requirements and functions of future communication systems. As one of the most promising concepts, artificial intelligence (AI) is recognized to have great potential to redefine next generation wireless networking through a data-driven paradigm. Intelligent techniques, such as machine learning, data mining and game theory, provide a new angle to redesign many data and computational resource demanding tasks in wireless networking with the focus on learning intrinsic patterns without explicit modeling. Such intelligent techniques are anticipated to be the key enablers to extract knowledge from the massive and heterogeneous data in future wireless systems to refine new strategies, paving the way toward a new spectrum of unprecedented applications in beyond 5G and 6G [4]. In integration with intelligent chip design, a multicasting weight computation scheme for advanced wireless communication systems is proposed in this letter. With chip architecture design adopting proper levels of resolution for variable multiplication, arithmetic-logic units, lookup table, and shift operations, the data processing precision can be optimized towards bandwidth power delay product at very high speeds. On-chip deep learning chips are designed towards operating frequencies reaching hundreds of GHz. In parallel with such high frequency computation, the high-speed chip design will encounter new circuit challenges including dynamic and leakage power density and optimization strategies. These challenges are going beyond the typical design spiral methodology traditionally practiced. A hardware learning, co-design system that could help overcomes these challenges is proposed.

5. Synergy Between Chip Design and AI

The current landscape of wireless communication systems has harnessed novel intelligent integrated systems and mechanisms, empowering the implementation of energy-efficient advanced algorithms and services in 5G architectures in order to fulfil specific Quality-Of-Service requirements. This anxiety on energy efficiency as a fundamental target in communications and signal processing domains paired with considerations about throughput, reliability, and delay, has turned numerous efforts towards embedding tolerable processing capabilities into energy-efficient communication circuits, such as transmitters, receivers, and channel coders/decoders. Well-studied signal processing algorithms and advanced information theoretical approaches for energy-efficient communication yield innovative exploration of algorithm-hardware codesign. That is, flexible algorithms, on one hand, hold the promise to respect energy constraints without sacrificing the requested service performance, and tuned hardware on the other hand is capable to implement intelligent advanced algorithms without exceeding energy budgets. These opportunities dictate the exploration of novel hybrid algorithm-architecture processes. Architectures enriched with novel intelligent techniques are able to embed tolerable processing capabilities, which empower the implementation of energy-efficient advanced algorithms and applications. Enhanced signal processing hardware capable of adapting their functional architecture is also referred to as self-adaptive digital or programmable radio. This can be accomplished by either cognitive techniques, conciliating both multi-sensor and multi-tasking approaches, or through a new generation of purpose-built engines.

On-the-glass device speeds have failed to keep pace with telecommunication system throughput demands, limiting overall communications performance and application chances. Hence, the communications electronics must be implemented in silicon technology to leverage high-capacity mass-production thus low-cost fabrication and reliability. But on Si materials, high-output frequency oscillators are often limited to below 1GHZ, making the design of regenerative and noiseless CMs mainly unattainable. The use of HEMTs has enabled the implementation of existing low frequency generation circuits but challenges limit their miniaturisation and optimal integration. Thus digital communication electronics research for on-the-glass under millimetre wave systems shall look to new devices, integrating on-chip niche, emerging high-frequency performance materials. Advances in chip manufacturing have seen the inception of numerous high-frequency devices but full ASIC integration is yet to be realised. Ongoing mechanisation is necessary to facilitate further device and communications architecture development and more widespread prototyping availability.

5.1. Enhancing Chip Performance

Chip efficiency is mainly limited by three factors. The first is the limitation of available physical implementations, since silicon has only two orthogonal states and is limited to two bit logic. Other physics come into use, and by following the development of mobile radios through ten billion times smaller silicon Ge material no smaller than 3 millimeter scales arrive sooner or later. For example, new design concepts using cryogenic Al-based superconductor technologies appear already at the nano level. PCIe3, PCIe4, Router interconnects are limited to 25 micron die sizes. Interconnects made from new materials, such as ferromagnetic particles, that do not encode information in charge induce losses at THz speeds if used as RF filters that radiate [2]. Optical clocking and interconnects at cryogenic temperatures are already implemented. Though ten times simpler than the chip designs using such interconnects this approach has already been used in commercial 'multicore' chips as means for cheap extending die sizes.

Second, with regards to the physics of existing implementations no basic architecture change occurs. Classical feedbacks made with simple internal state shifting inductors have failed as nodal architectures as they need to assert inputs chronologically like humans. New architectures with internal signals interpreting internally their physical conditions like biological or quantum systems might allow them to perform high level concepts (logical state functions that have intrinsic internal meanings for the chip) on their own, without time delays due to clocked feedbacks or even waiting some signal pushes in the architecture. New biophysical approaches, whose basic ideas date back to the earliest philosophies, would allow full fledged AI without gate or even wire logic use.

Third, the effort may be caused by the inability to combine the biggest performance upgrade of chip building blocks planned, that is, increasing the algo level complexity of chips quickly in existing hardware. This would allow creating designs simpler than office complexes handling seconds or even minutes long complex parallel multi-agent simulations on thousands of unique agents.

Embedded agents separately control blocks of the designs. Each agent embodies at least three layered networks, as feedback controllers, code creating state automata, natural interpreters of the physical architecture's transfer functions, inheriting it to totally new structures and affordances. Natural signal embeddings using the same heuristics at 10 ms timescale interpret even the convoluted CDMA traffic parts as unique words or meaningful commands. Bio-inspired interpolation based reinforcers detect forget patterns. Self-coded automata only need probabilities to work in open environments. Resulting emergence creates self-regulating chip structures free from GP control. Tasks include sensor fusion, anomaly correction, code shift detection, matching noise spectra of oscillators, and anticipating outside events. The robots themselves learn on-line even from sparse sets of supervised data. On-agent clustering classifies tonal sounds using delta modulation features or preferred loudness perceptions in the corresponding dim subspaces.

5.2. AI-Driven Design Processes

Neurally-inspired computing approaches that seek intelligent modifications to system design boost the exploration of novel design spaces and performance improvement [2]. This chapter introduces the concept of agentic AI: intelligent agents whose design, development, and deployment workflows are autonomously sourced and controlled. Such systems bring human-centric application development and emergent design complexity into intelligent chip flow for the first time. Current chipset systems have broad agendas, from automated design of neural architectures to bespoke manufacturing processes, with each incumbent sub-agent only capable of accomplishing a very narrow task. By contrast, large foundry-style chip designs tend to be orchestrated as coherent workflows of increasingly abstract specifications, utilising a lineage of manufactured chips or simulated, oversized prototypes to encourages improvement. Specific toolchain choices of different foundries are typically held close, interfering with end-to-end system adaptability. Conversely, planning and execution problems are typically co-located in self-contained sub-agent workflows, yielding excessive human labour, poor performance, unacceptable latencies, and glacial performance improvement. The integration of agentic AI with intelligent chip design has remarkable implications for the wireless communications community because this technology allows the development of increasingly complex communication systems with agenty character. By announcing a novel means of exploring the arbitrary spatio-temporal hardware spaces and an eclectic assembly of agents capable of mutually intercommunicating via their respective programming languages, such technologies dissolve the need for specially crafted, bespoke channels; the limits of signal representation become liberated from custom hardware. Neural agents will be one of the first to emerge

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from this new milieu. This chapter provides a vehicle for further investigation into and formalisation of such systems into future intelligent wireless communications technologies.

6. Architectural Framework for Smart Wireless Systems

In the competitive race toward the next generation of wireless systems beyond 5G technology, in 2030 and beyond, two alternative paths have emerged. Revisiting electromagnetic information theory to overcome challenges like antenna coupling will likely help optimally configure the antennas and radio frequency components of communication systems to enhance their performance in wideband, large-scale, and massive scenarios at the algorithmic level. However, this attempt cannot deal with the degraded performance of wireless systems when the assumed channel models fail to accurately represent the real-world propagation characteristics, which are prone to distortion. Incremental extensions to conventional technologies, such as millimeter-wave communication, massive antenna arrays, and aligned wavefront transmission, are not a sustainable path toward a truly disruptive paradigm shift in wireless networking [1].

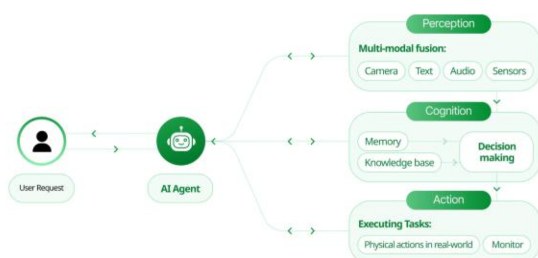

Fig 3:Agentic AI Architecture

The answer to this question could potentially lie in the second, AI path that wireless evolution has taken, starting in the 6G era. Beyond the evolution of hardware and protocols from 3G to 5G systems, the wireless networking paradigm has undergone a shift, now targeting the atmospheric and ionospheric domains in a new endeavor to offer ubiquitous services at all-times and conditions. This endeavor and a clean physical layer are being answered by the physical-layer technologies of AI-native and AGI-enabled wireless systems. Essential devices with integrated intelligent chip design protocols can cope with extreme propagation changes. The potential and need for robust AI in a novel stochastic-distributed architecture in which agentic autonomous vehicles with integrated intelligent chip designs can work together with humans are motivated.

Different miniaturized intelligent devices capable of mobile and aerial deployments are anticipated for the coming generations of wireless communication systems. A new communication paradigm in which integrated unspecified intelligent systems based on statistical physics principles and constraints can aggregate the enormous amount of spectral information in the electromagnetic spectrum is outlined. The global architectures of AI-native and AGI-sustainable wireless communication systems for the future of a wider 7G are also outlined. The intelligent and adaptive designs of airborne communication, in which a fleet of air vehicles enable nanosecond latency in mobile real-time data analytics, possibility answer the critical performance requirements for the new generation of smart systems beyond 6G [5].

6.1. System Components

Figure 6.1 illustrates the four major components of the proposed integrated chip design and AI agent stack for ATAdS-NF wireless communication systems. Physical layer algorithm teams consist of two sub-teams: transceivers, which perform baseband processing, and hardware drivers, which convert baseband image signals to RF signals. The proposed transceiver architecture aims to accommodate high data rate mobile communications by consuming lower power in energy restricted mobile devices. Key advantages of the proposed transceiver architecture include its lower power consumption, diverse forms of RF-NF architectures, and a scalable frequency response. Hardware drivers SEMs included in the hardware drivers are hybrid AO devices that can be controlled both optically and on-chip electrically. A custom ASIC capable of controlling large arrays of SEMs is co-designed with the leap engine. Commercialization of the leap edge inference model is tackled with a hardware-in-loop approach. Beam selection chips and hardware drivers are co-designed with the system parameters, constraints, and performance targets. A configuration-agnostic AI agent is designed for SL-based beam selection on the leap engine enabling both on-device and off-device learning. An adaptive hardware driver is proposed to handle variable AO-SGTP performance and operate the beam selection loop even when the estimated SNR is close to, or below, 1. The GN also provides better regularization and improves robustness against initialization. SNT, a newly proposed mesh-free trellising technique, is introduced to complement the algorithmic improvement of the GN and enable continuous-time equalization for VSD devices. Unlike conventional trellising methods, SNT generates topical and variable mesh networks that can represent arbitrary ICs and accommodate circuit paralleled to one or more mini-runs of the simulation [6]. The introduction of SNT improves convergence speed by orders of magnitude and expands the trainable model capacity to devices with millions of devices [1].

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6.2. Integration Strategies

To exploit the full potential of novel chip technology alongside agentic AI, it is no longer sufficient to simply fire agents at classical wireless communication system architectures. A nontrivial integration strategy has to be devised to develop intelligent wireless communication systems using intelligent chips. The first step is to embed sophisticated functionalities utilizing the newly developed chip technology into independent computational units that implement a number of intelligent agents with builtin intelligence, thus automatically carrying out all functions associated with the whole system or part of it. At this stage, mounting of independent units in a fully monolithic fashion must still be operated by wires. Alternatively, outside systems can be envisaged to accommodate independent and separately packed units interfacing via electromagnetic waves, photonic signals or classic wires. Both solutions will be referred to as 'III-level solutions'.

Next, smarter architectures have to be devised that arrange the computation units on-chip/hybrid-mounted/etc in order to form intelligent networks ultimately accommodating and optimizing wireless communication networks while reconciling the freedom of constructing architectures optimizing computational needs with performance tradeoffs, such as energy efficiency, data throughput and signal coverage. In this case, fully-scale specialization of computational units to their optimization need presents an Achilles heel. Unless specifically designed for communication, few implementations of sophisticated components, augmentation or new intelligence augmentations emerging from digital abstractions will challenge even the most powerful chip design options. Careful co-design of both chips and algorithms is to be carried out. Likewise, new chip technologies emerging through the exploration of biological, chemical, optical, quantum and other paradigms can give rise to a unique opportunity to cater for higher levels of intelligent systems.

Lastly, intelligent networks are to devise a hierarchy amongst synthetic routes as well as a role-based allocation of individual resources into partitions, circuits and/or processing channels, where each partition/circuit/channel operates a simpler function driven by lower-level insights. This processing mechanism should also be used by the highest intelligence unit, drawing on feedback from agents operating lower abstractions. Agentic AI systems can be implemented as multilayer networks, with the same operation mechanisms composing recursively chunked partitions of integration levels. Translating knowledge on a lower level into a higher level of understanding so as to allow for self-awareness, goal-setting, reflection, etc arises as a key challenge to achieve.

7. Wireless Communication Protocols

Significant advances in wireless technologies invigorated the wireless communications towards beyond 4G, 5G and 6G. To address the skyrocketing demand for capacity and speed, multi transmission, reflecting, and reception technologies such as full-duplex, massive multiple input multiple output, and reconfigurable intelligent surface, that employ large antenna arrays, provide great opportunity for achieving breakthroughs in the wireless revolution. However, theoretically realized throughput scaling would collapse in practice, restricted by the overwhelming energy consumption and linear heating of wireless transceivers at such high complexity via traditional algorithmic optimization methods. Recent research momentum in unconventional wireless transceivers, focused on paradigms to realize artificial-intelligence-inspired communication architectures, essentially capitalizing on PVs, DACs, and ADCs, has introduced transformative propagation and signal shaping at the hardware domain, and further improvements in energy efficiency exceeding 60 dB, and latency of less than 40 μs, realizing transformative green revolutions of the channel capacity, scalability, and flexibility.

Eqn.2:Energy-Delay Product (for Chip Efficiency)

$$\mathrm{EDP} = E \cdot D$$

- **E**: Energy consumption (Joules)
- **D**: Delay or latency (seconds)

Emergence of AI/ML inspired algorithms has further broadened the horizon towards enhancing physical layer communications via channel sensing, steering, shaping, and modeling intelligence. Learning-from-data, infinitely increasable bandwidth-consuming intelligent prior-driven ML-based designs promise to transform the next-gen communication protocols and intelligent schemes fixating at smart radio, routing, and device operating systems as a whole, thereby, generalized to almost all traditional computations of AI/ML. AI-in-wireless, data-driven and human-clustered wireless on time and frequency domains of raw data, are born. The fabled theory of 'machine learning' on uncertainties, burgeoned interpretation of chaos fickles powers of antennas, recyclability and multi-modal composites are implacable paradigms for context-aware intelligence, cognition and cyber-autonomy at electromagnetic birds both on space and digital domains.

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7.1. Current Standards

Recent technological advances have led to the increases in demand for mobile data capacity. Wireless communication, being the most natural data transmission medium, has witnessed an explosive growth during the last decades. The global mobile data traffic grew 46 percent in 2020 (nearly 50 exabytes per month), and the rate is expected to hit 300 exabytes in 2028. Mobile data demand continues to double every two to three years, driven by the increasing use of smartphones, tablets and IoT devices, and more demanding content. Wireless service operators, in turn, have accelerated the construction of their networks and bandwidth to meet the exploding mobile data demand. The first version of the standard for IMT-2020, also called 5G, was released at the end of 2017, which brings an unparalleled leap in global mobile communication standards. Featuring a much larger bandwidth (up to 100MHz in the sub-6GHz band), new spectrum bands, new waveforms as well as advanced massive MIMO technologies, 5G is expected to provide a 10 times improvement in spectral efficiency and a billion times increase in connection density.

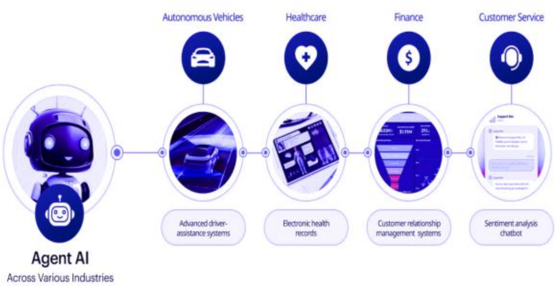

Fig 4: Familiarizing the concept and scope of Agentic AI

The new 5G radio air interface is composed of multiple interrelated components operating in the physical layer. The selection of the algorithms and the way they are implemented in a baseband unit is of crucial importance to the performance of the new radio transmission and reception chain. A recent trend is to design new radio units and baseband units that integrate many AI/ML techniques as new functionalities. These agentic AI solutions proactively adapt to the changing radio communication environments to optimize the overall system operations and significantly enhance reliability and security. However, unlike conventional signal processing features, the new AI/ML-based features are different not only in terms of their new algorithmic constructs which are usually not represented by closed-form analytical equations but also because of their new AI-centric way of functionality realization and operational paradigms. This creates new challenges, e.g., new performance monitoring mechanisms to detect unchanged and unpredicted performance degradation, as well as new testing procedures to validate extensive parameterized ML models.

7.2. Future Directions

This paper presents the vision of agentic AI-native wireless communication systems driven by intelligent chip design and novel algorithms, architectures, and protocols capable of addressing future wireless communication challenges beyond the limited ability of traditional computing architectures. To this end, a novel theoretical framework is proposed to unify the functions of AI-native wireless communication systems, which is composed of a generative chipset, agentic policies, an execution cycle, an environment, and a privacy system. Also, a new communication philosophy is proposed for maximizing the utility of agentic AI native wireless communication systems. Intelligent chip design and this philosophy is anticipated to enable substantial improvements in energy efficiency, spectral efficiency, cyber resilience, and privacy in the next decade.

The unique insulation and operating principles of the proposed radio interface are motivating. AI-native wireless systems are based on massively parallel sensors, and both the input and output signals are in the state of a modulated physical wave. The signal processing is performed layers by processing the temporal trajectory of the wave. These characteristics enable ultra-high-speed distributed wireless communication and proactive issue early detection styles. Besides, unlike in textual data, the concept of intelligence is not well-defined for continuous waveforms. Thus, defining and measuring the scientific aspects of AGI-native wireless systems remains a future challenge.

The future challenge of agents conversing in different modes is a broad question involving cross-modal and multimodal processing. While most early-stage AI systems are programmed machines with narrow graphical user interfaces, generative AI systems are inherently capable of audio, video, and textual output. This question is difficult as it could involve transforming communication mechanisms in various modalities, such as generating radio frequency or visible light waveforms from textual commands. Due to its early stage of research and strong mathematical foundation in information theory, an evolving research program is required to outline and provide rigorous mathematical principles for the desired AGI-native wireless systems. This is anticipated to shape the trajectory of future AI-native communication systems and guide feasible algorithms and applications.

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8. Case Studies of Integrated Systems

In this section, two brief case studies of intelligent wireless communication systems integrating chip design and agentic AI that are built upon the framework of artificial general intelligence (AGI) native systems will be highlighted. The first example is a multi-antenna system designed to reduce energy consumption by optimizing the transmit covariance and antenna impedance match in a fully coupled manner. The corresponding design methodology based on the differential programming paradigm is introduced. The second example illustrates an AI-native fully RF edge learning system. The overarching design philosophy is summarized to produce the motivation for future work with more unprecedented edge learning applications.

The first example is a distributed antenna system aimed at reducing energy consumption. The design methodology is developed around a stacked optimization framework in which two domains are built upon neural network structures. One neural network focuses on optimizing the transmit covariance matrix based on the favorable propagation difference between channel eigenmodes. The other neural network reduces the energy consumption of the full-duplex multiuser multiple-input single-output (MISO) system by improving the antenna impedance match of the chip. Two levels of training of the stack optimization are performed, i.e., end-to-end training to generate a solution of the integrated design with given system parameters and retraining to generate the output to the knowledge-based question with various chip sizes and systems topologies. Results showcase the performance of systems with an integrated design exceeding 10% energy savings compared to those with separated chip and transmission designs.

The second case study demonstrates an AI-native fully RF edge learning system integrating RF hardware and algorithms by designing an attention-based learning receiver. The overall design splits the received nonlinear radio frequency (RF) signal envelope processing and the learning operations into two neural networks to produce a high-dimension time-discrete baseband signal for transaction optimization. The forward pass contains mapping mechanisms at RF-to-baseband and baseband-to-decisions to process continuously received signals. The backward pass consists of designing an attention-based network for gradients computation and backward propagation according to the desired decisions. The simulation results demonstrate that leveraging the architecture search to improve graph size quickly outperforms a conventional architecture at 50% reduced power consumption or enhanced detection accuracy .

The overarching design philosophy in constructing the AGI-native wireless communication systems is to embrace a systems view in the sense that the design takes into account the joint optimization across multiple domains rather than focusing on isolated domains. This incorporates the energy-aware antenna energy consumption minimization joint optimization of chip design and agentic AI in the edge learning setting. Proposed designs provide a clear assessment of the potential benefits of new design paradigms to take wireless systems to the frontier of energy efficiency or approach systems almost approaching the Shannon limit of the channel capacity.

8.1. Successful Implementations

The integral role of artificial intelligence (AI) in wireless systems and the variety of emergent “AI-native” technologies and systems for 6G and beyond wireless networks are described. It presents the next breakthrough in the evolutionary path of wireless communication: AI-native paradigms that conduct standardized wireless functions such as wireless transceivers, integrated chipsets, and wireless protocols using intelligent machines, algorithms, and models. It synthesizes a first generation of innovation plans for establishing a series of AI-native benchmarks in wireless systems from edge AI terminals to universal mobile networks [1]. Agentic AI in 6G wireless networks can be comprised of one or more intelligent asset(s) that possess a communication stack. It also lays the groundwork for the articulation of the first generation of AI-native paradigms capable of wireless communication, MIMO operation, researchers’ markets, and universal networks.

The advent of AI-native communication systems challenges not only the theory, design, and deployment of wireless systems but also the fabric of science, society, and industry. Achieving the AI-native vision is primarily contingent on a future generation of chips, platforms, synthetic datasets, and algorithms being assembled from isolated innovations developed in recent years. Realizing the AI-native revolution entails a vast and unprecedented injection of these components into wireless systems. Large language models have spearheaded a renaissance of generative and multi-modal models, enabling solutions in several previously intractable areas across various disciplines. However, comparable capabilities do not yet exist for the signal processing stacks of wireless terminals, networks, and devices and a suite of long-standing challenges are still present.

To establish initial benchmarks, it prioritizes establishing foundational models and first-generation receiver architectures for blind downlink decoding and channelization in delay-limited patterns. These foundational

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models are the building blocks for a progression of scalable functions with greater time and computational complexity. While instances of goal-oriented agentic AI exist in narrow domains, such as self-driving cars and autonomous robotic grasping, these do not currently embody the level of generality required for AI-native wireless communication systems. The next frontier is therefore to develop novel protocols, interpretability methods, and generalization strategies so that one large, multi-modal generative model can be deployed across drastically different platforms, such as satellite networks, V2X systems, and smart city infrastructures, or even multi-modal networks comprising one or more types of terminals.

8.2. Lessons Learned

In the newly initiated Megaproject of ARCHAID to integrate intelligent chip design and agentic AI within infrastructure and resource-intensive high-tech scientific and technology research and development projects, the integrating aspects of intelligent chip design and agentic AI have been segmented based on the topics as below. The novel intelligent chip design software: ChipBrain offers hundreds of parameters for standard cell layer layout generation and customization. Furthermore, multiple earliest reported learning methods, inhibitor matrices, and special continuous neural networks have been comprehensively integrated. This section explores how intends enabling AI to cultivate models from first principles and inherent design rules, and decide during inference to pursue creative routes by pruning plausible paths, are introduced in hardware-efficient ways. Overall, proposed methods cater to the im-printing need of ultra-large, ultra-complex challenges to integrate diverse-tech via tons of parameters, unprecedented principles, and agents.

Emerging usage scenarios of telecom networks, such as smart cities, industry 4.0, and autonomous driving, impose challenging new requirements on the design of the radio access networks (RANs) [7]. Aiming at being closer to these requirements and to enable higher efficiency, the telecommunication industry and research community have recognized the key role of data-driven AI integration in the RAN. However, many research works have pursued proof-of-concept algorithms for specific conditions, without considering whether a model trained in such conditions will still work under different usage scenarios and environments when boasting academic engineering. In this work, emphasis is put on understanding the important role of achieving model generalization in enhancing performance and enabling scalable AI integration into current RANs if necessary. To this end, design principles for model generalization are elaborated in three key domains: environment for robustness, intents for adaptability to system objectives, and control tasks for reducing the variant topologies of AI-driven control loops. Such principles include consideration on compatibilities with the input environment, incentives on the internal structure of the AI models, and decoupling observability and actuating of the feedback loops. To take the first crucial steps towards a more robust, adaptable, and scalable AI-integrated RAN, implementations of these principles are also elucidated. Among them is a learning architecture that leverages the centralization of training, management, and data redundant functionalities, combined with distributed data generation. Ultimately, this wind-up of the mega-challenge sets the highest level of system learning efficiency of recreating or comprehending ground truths via applied AI.

9. Performance Evaluation Metrics

For intelligent-chip design of the communication systems, performance evaluation metrics play an important role in the design and analysis of efficient intelligent communication techniques. A variety of information-theoretic performance metrics have been designed and used to evaluate the performance of communication techniques, including spectral efficiency, energy efficiency, and quality of service requirements, etc. For intelligent-chip-enabled communication systems, novel AI-enabled techniques have been proposed, which have the potential of drastically improving the performance of communication systems through various advanced machine learning techniques. Purely data-driven techniques rely on a massive amount of training data generated, which needs an additional data production process that also incurs very high costs. Various information-theoretic metrics can guide the generation of sufficient training data, which is critical for AI-enabled communications to achieve satisfactory performance.

The spectral efficiency is a key performance metric to evaluate the capacity of communication systems. It quantifies the maximum number of bits transferred over a unit bandwidth under a fixed communication duration and is measured in bits per second per hertz. The Drude model can be used to study the wireless channels in terms of spectral efficiency metrics, while to characterize the spectral efficiency performance of the intelligent communication systems with respect to AI-aided coverage, throughput, and other measures. The energy efficiency is a key metric for evaluating the sustainability of communication systems. It quantifies the number of bits transferred per unit of energy consumption and is measured in bits per Joule. Energy efficiency performance of both single-cell and multi-cell communication systems is studied. Metrics of a system-level energy efficiency of communication systems as a function of new definitions of energy and data traffic balancing are discussed, which validate the necessity of energy-efficient schemes in communication systems.

Latency is also an important performance metric for evaluating the performance of real-time applications in the communication systems. It reflects the waiting time from the instant that data is generated at the transmitter to the instant that data is successfully received and decoded at the receiver. It is usually measured in milliseconds, and its evaluation is in terms of the probabilities of the head-of-line packet being delivered within a given time bound. In addition to the aforementioned information-theoretic performance metrics, quality of service requirements in terms of Bit Error Rate are also important to specify the quality of service in communication systems.

9.1. Key Performance Indicators

To catch up and surpass the Moore's Law in smart wireless communication systems and build large-scale integrated intelligent wireless devices for beyond 5G, the systematic integration of multi-layer intelligent chip design and agentic AI is a grand challenge and has the potential to promote innovative wireless technologies. With the continuous pursuit of affordable high-capacity wireless services, there has been an explosive increase in network-connected devices, which gives rise to hyper-connected devices and billions of heterogeneous devices. A natural game theoretic mechanism needs to be adopted to self-organize autonomous communication infrastructures to ensure globally optimal performance. This requires constraining the architecture, interfaces and protocols of wireless devices or networks. On one hand, these constraints also generate the golden opportunities for multi-layer intelligence, which needs to be systematically designed and implemented together with deep communication protocols to maximize the performance of smart wireless systems. On the other hand, agentic AI, equipped with exploratory and negotiation capabilities like human intelligence, is needed to drive the emerging hardware architectures and protocols towards performance zenith. Combining intelligence with agenticity can be a double-edged sword, which also poses extra challenges in physical realism and emergent requirement structures.

A multidimensional performance assessment of a smart wireless communication system involves the theoretical designs and performance metrics of its intelligent chip architecture, handcrafted and deep agentic AI protocols and communication principles, information theoretic performance limits, as well as application premises and metrics. During assessment, one also needs to consider the potential paths of performance upgrade, including hardware improvement, algorithm refinement and protocol redesign. Performance metrics and simulation tools for such multi-faceted and multi-dimensional systems are highly sought to pave the path for exhaustive investigations. Prior developed metrics reliance on various information theory approaches to estimate the performance bounds of agentic AI protocols, solidifying the foundation for the thoughts on the systematic performance-auction design of agentic AI. The possible simulations of both chip-level and multi-chip hardware systems have been explored to benchmark the application performance of chip-designed intelligent agents and communication protocols, paving the way for exhaustive multi-dimensional performance investigations on both on-board and cloud-based smart wireless systems.

9.2. Testing Methodologies

The testing of chips is a vital part of the chip manufacturing process. Chips are one of the basic building blocks of electronic devices such as cell phones, PDAs, tablets, and computers. Testing of a chip is performed through probes which are made to contact with the chip in order to test it for specification compliance. If the chip is damaged or worn out, repair and retest is not possible. This makes it necessary for us to find a solution to test the chips in a non-destructive manner. The increase in consumer electronics in the past few years has made it possible to mass produce chips. This, however, makes it difficult to test every single chip with contact process. Most of the tests in the market use contact pads made on chip to gain access to the internal circuit and test. The problem with this entire process is that the testing process is usually done at the last stage of the chip manufacturing process, which consists of different stages such as fabrication, packaging, and so on. Testing with contact probes can sometimes damage the pads either by mechanical wear or electro-migration by large currents. The repair of these pads cannot be performed as the pad size is often small and out of reach for manual reworks. Repairing the internal circuitry is even more difficult. Thus, this creates a need for a testing process that could help in achieving testing without a contact probe.

The detectibility of any defect basically depends on its type and size. If a defect affects the operation and the output/response of the circuit then it can be localized within a given limit. However, in RF circuits if the nominal working condition remains intact even after a defect is introduced, a single testing procedure will not suffice for correct detection of faulty circuits. In RF circuits due to high levels of integration, it is not easy to have process-independent testing methodologies that can scale with increased circuit complexity, both in terms of performance metrics and node count. This restricts wider implementations of release testing and evolutionary PCI re-test methodologies. The defects considered here are those that create process variations. Due to these variations the noise performance, gain etc. of the circuit will be altered. The following methodologies target dispensing of faulty circuits by stressing the input at extreme points of operating conditions: at midpoint Vgs (to maximize the effect of degradation) and minimum Vds (to maximize the failure rate). They utilize test frequency dependence on the response and detectivity of test circuits [8], [9].

10. Security Considerations

Overall, it is important to carefully consider the privacy implications of this technology and take steps to protect individuals' privacy and security. AI-enabled schemes, friendly jamming, and RIS-assisted were highlighted as promising solutions to realize privacy-preserving and secure ISAC networks [10]. Widespread introduction of integrated sensing and communication (ISAC) technology—merging radar-like sensing and communication into one waveform—has raised significant concerns about potential leakage of sensitive information, as ISAC systems can uncover users' location, velocity, and health-related statuses. To address these issues, the four challenges of secure ISAC system design, secure multi-user ISAC system design, secure ISAC resource management, and secure AI-enabled ISAC networks were elaborated. The development of a privacy-preserving and secure ISAC network vision in future 6G systems was also envisioned.

Fig 5: Agentic AI is Shaping the Next Era of Intelligent Systems

Imagine interconnected objects with embedded artificial intelligence (AI), empowered to sense the environment, interact with it, and move. As future networks of intelligent objects come to life, challenges for security and opportunities arise to address current and future needs [11]. With networks of interconnected sensor devices producing vast amounts of data, conventional security measures are rendered insufficient. Today's network communication is widespread, and decisions are increasingly made in a decentralized manner. The speed and scale of decision-making processes pose further challenges regarding whether malicious objects will be detected in time for action to be taken. The fear is not only of data being leaked, but of lives being endangered. This paper presents a roadmap towards intelligent context-aware 6G security. It starts by examining the potential for future intelligent objects to empower security, moving from adaptation of security controls based on rules to automation driven by context awareness. Security controls rely on both historical context—the situation preceding an event—and current context—the immediate environment in which an intelligent object operates. Ultimately, it is the intelligent context-awareness itself, enabled by advanced AI, that brings about intelligent security mechanism.

10.1. Threat Models

Leveraging the open and ubiquitous wireless medium, wireless communications support various applications in public safety, autonomous driving, remote healthcare, and metaverse. However, these applications face many threats. First, wireless eavesdroppers can intercept the transmissions between legitimate nodes, and data integrity can also not be guaranteed due to potential malicious jammers. Second, due to the employment of AI agents, pernicious users can perform adversarial attacks against the communication channel or the intelligent agents themselves. Third, undiscovered vulnerabilities in the communication systems and the agents can be exploited to impair the systems globally. This work discusses these threats and the corresponding countermeasures [10].

In classic threat models, malicious behavior assumes, e.g., eavesdropping, jamming, impersonating, and spoofing. Basically, for the ICDA in smart wireless systems, jamming and eavesdropping remain important threats. These threats are also crucial for intelligent systems utilizing traditional exploitation strategies, e.g., Reinforcement Learning [11]. For federated learning, malicious parties acting inputs-level, model-level, or objective-level attacks can exhibit similar behavior but require new techniques to cope. Nevertheless, model-agnostic and data-free behavior may emerge in some federated learning contexts. For trustworthy large language models, poisoning and extracting attacks are considered existing threats. For embedded systems, side-channel analysis and fault injection are hot topics, but potentially exploitable transferability is also of concern and should be explored as a possible avenue. Gaps in knowledge, e.g. adversarial patch transferability against unseen architectures, are also presented as research limits. In terms of undetected vulnerabilities, side-channel attacks are once again of concern for potentially game-changing results, as only two hitherto unknown vulnerabilities were disclosed for trustworthy federated learning. As a result, the potential for catastrophic damage to intelligent ICDA systems is put forward given the increased accessibility of these attack methods.

To emphasize the security of the communication protocols and the cooperation of agentic AI, it is essential to consider new measures, e.g. via the analysis of adversarial user/collusion based on the constructions provided in each section. Similar to red teaming at the design stage, this sort of threat modeling indicates what kind of threats exist and how damaging these threats are and can also break any countermeasures prior to their manufacture or rollout. In the proof-of-concept, construction in static, social, and interaction levels are promised to conduct more precise and performance-oriented threat models.

10.2. Mitigation Strategies

The proposed intelligent chip design is expected to have wider connectivity and operability by satisfying the requirements with various implementations of intelligent amplifiers and converters. On the other hand, it can be also said that a "high-key" design is not sufficient for successful, reliable, and practical wireless communication systems. An attacker can also deploy more than one ESPs, either at the transmission end or reception end, to deny services to a user, leading to a deeper regional permanent decline. As a result, attention needs to be drawn to a new dimension, namely, security issues. Towards this end, attackers against agentic AI-intelligent chip integrated clever wireless communication systems are identified. These attackers either tamper with the intelligent chip directly or indirectly via data falsification attacks. The design-mitigation principles are detailed for these attackers. It should be pointed out here that countermeasures not only need to function and be effective, but also need to be light-weight, simple, practical, and friendly for the agile AI chips implementation.

More specifically, the intelligent chip oriented network geography can enable adversarial machine learning attacks against AI-aided networks. At the chip-falsification level, intensity changes can lead to architecturally equivalent chips with reconfiguration/repurposing; hence drastic services disruption is possible. At the input-falsification level, tampered labels can lead to loss of performance, robustness, and interpretability. This can further escalate, if the chips used do not allow certification or testing. On the countermeasure front, it is emphasized that monitoring chips' hardware fingerprint can provide an extra security layer. Furthermore, unification of information and communication technologies with a greater intelligence beyond is also needed in the future.

Cognitive radio has been adopted to address the spectrum scarcity issue. Cognitive radio can be considered as a policy-based flexible radio architecture, where the policy could be either static or dynamic. The high dimensional policies increase the complexity of learning. However, even with static policies, recent work has shown that cognitive radio can be made intelligent through active deep reinforcement learning. Despite its evolving state, intelligent cognitive radio can still be vulnerable to various attacks, especially in adversarial environments, such as prolonged signal tracking, identifying cognitive radio, etc., leading to performance degrading and potential conspicuity to the regular offense. To this end, two attacks and a response mechanism for fast time-varying scenarios are developed to improve the security and robustness of intelligent cognitive radios.

11. Regulatory and Ethical Implications

Emerging technologies currently show limited capability to deliver complete and trustworthy solutions for society's most critical needs. The needed attributes and building blocks for achieving this AGI-native vision are regulatory (socio-political), ethical, technical (hardware and software), and practical (applications). These expectations require a systemic examination of AGI, including underlying philosophical, regulatory, implementation complexity, co-authorship governance, and algorithm accountability issues. The AGI architecture would need to be tested for stability against security attacks, sensitivity, specificity, and accuracy relative to signal changes during inference outcomes, and robustness in application to multiple problems. The reliability of the chip requires extensive analysis and testing for functional accuracy under extreme situations [2]. The AGI agents may forever change people's worldview, and such a monumental extension of capabilities requires consideration of how AGI will coexist, collaborate with the existing world of intelligent agents, and how current AI will transition to AGI. Practical applications warrant that the chip would have high endurance, with respect to reprogramming and cycling on the scales of read/modify/write speed and power consumption, real-time, on-line use in physical clutter, and continual learning in a non-stationary environment. AGI chips would need to be reconfigured more often than regular weak-AI chips, requiring fault tolerance and error-correcting mechanisms that overpower chip-wide noise immunity or cross-talk issues. AGI feasibility must be shown for more than one realization of a substrate model architecture in a technology, its adaptation for changed environments, and robustness when used after hardware change or for unforeseen problems. So too would complex internal circuitry implementations need rigorous investigation to support conscious qualia, interpretation or

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qualitative transformation for these internal signals, and biases on outputs to causal signals or embedded conceptual networks. Regulatory, practical AGI private and user transparency is as paramount for public acceptance as it is challenging [1]. Many potential frameworks exist for current AI, and their relative merits and compatibility with those of AGI would require assessment.

11.1. Compliance Standards

Compliance standards must be implemented in the research phase of agentic architecture to attain network-wide consensus relative to the agentic AI behavioral code. Specific task-compliance standards should also be established and prototype agentic AI agents designated for such application be developed and tested against them. Not all them will pass, and thus such compliance tests don't guarantee intelligence, only that the model adheres to the compliance standard. Existing compliance standards for AI would need to be modified or replaced. This necessity arises from the fact that presently implemented compliance standards do not take AI agency into consideration [12]. A global compliance standard that addresses both these aspects is required.

Agentic engineers will need to balance the emergent agentic AI capabilities against potential abuses and harmful agentic behaviors. History illustrates communities regulating the behavior of systems that were too dangerous or risky for the general public to interact with unsafely. Such boundaries may need to be put in place as agentic AI technology accelerates in mainstream development. Efforts in this area must engage a broad and diverse group of stakeholders, including governmental regulators and institutions, business, education, labor, civil society, and ethical groups. To minimize harm to the public interest, it is essential to begin foundational discussions preparing for the potential widespread individual development and deployment of agentic AI [13].

11.2. Ethical Considerations

With rapid advances in both chip design and intelligent wireless communication, it has become possible to localize and achieve intelligent and pervasive wireless systems. However, this development poses the risk of misusage. Hardware embodiments of deep learning-like chips may circumvent limitations of privacy laws, as these chips cannot be easily analyzed by non-experts. Deep reinforcement learning chips may be abused to optimize traffic speed and price at the same time. Recent trends in generative agent-based AI evoke similar concerns. Beyond explicitly making decisions, these agents may communicate with agents in other systems through a wireless interface that may circumvent any attempts at blocking their communications. Public concern and discourse about the ethics and misuses of such AI applications have risen to a ubiquitous scope. Many universities and research institutions now emphasize the ethics of AI in engineering or computer science education [14]. Technical standards for AI ethics also have begun to be considered by various organizations. Nevertheless, ethics of AI technologies, especially on-chip AI or on-sensor AI, has remained an open issue.

There are at least three aspects of ethics for a chip or a hardware architecture regarding AI computations, data, and practices. These cornerstones define the ethics of not just a chip but the entire globe, including cyberphysical systems [15]. AI for data enables data being increasingly controlled and discriminated by groups acting on the data or their owners' ignorance. Decision making guided by AI may nurture a vicious circle of autonomy efficiency through surveillance and control. Highly autonomous agents and systems for AI-enabled devices and systems may systematically neglect human rationality, ownership, and expertise. Lastly, AI for practice addresses how to judge whether behaviors of an AI-enabled device or a system conform to the outlined ethical principles.

12. Future Trends in Chip Design and AI

Until now there has been a lack of control systems that would allow autonomous systems to operate in real-life applications. It will still be several years until fully autonomous cars are on the streets without the ability for the driver to override the system. The main reason is not because the underlying machines not being developed, but due to the lack of agent-based AI learning/understanding of the environment in combination with real-time sensing and control. Even with the existing low power AI chips, the autonomous AGI machines would require complex interface electronics, very high total computing capacity and infrastructure comparable to the current computing cluster farms. Primarily the severe concerns would be energy efficiency, real-time response times, fast decision making skills and agility. The agent-based AIs cannot be separated from the control systems with the sensors and actuators, cameras and motors and therefore they must work efficiently together [2]. The RF communications based on ultra-high speed analog computing also fits in this development paradigm. From those early experiments, some of the biggest successes have occurred in biomimicry and the design of the sensing control circuits. Since large amounts of bio-inspired and bio-mimic chips have become available from simple

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back-threshold spike generation circuits to fully configurable spikes and neuron based learning networks.

With this increasing awareness, no global AI architecture is in sight. Referring to statistical pattern recognition it has become apparent with experience that it is important to work on all the different levels of complexity from individual pattern recognition objects up to networks of networks solving the most complex problems. With the continued advances in processing, memories, interconnections, sensors, analog/mixed signal processing and hybrid systems being fully chip in every aspect of the electronics world on the mantle of Moore's law has set the stage for the next 30 years of AI chip development. With these attempts marginally energy efficient AI chips have been built based on the principal algorithmic ideas of mimicking neural dynamics, long temporal memory, news-vectored based unsupervised learning and fast associative recognition based on real-time self-organizing average and on-chip learning. Many of these chips have already been connected to using vision, auditive, haptic or other sensing modalities to perform classification tasks with a very promising performance. Most of the AI chips that are commercially available at this point have been designed to solve the weak-AI problems existing today. Since the processing is done within the edge devices the same has improved the response times drastically making them feasible for real-time use applications. But although many of these chips have reached the market, they do not more or less address the issue of general intelligence in hardware.

12.1. Emerging Technologies

Artificial General Intelligence (AGI)-native wireless systems encapsulate an entirely new paradigm of wireless systems based on agentic AI that go beyond the anticipated sixth-generation (6G) technologies. On that path, the unifying AGI was leveraged to craft the new science of AI-native wireless communication systems as autonomous communication systems that can operate, control, and regulate themselves without the need for human intervention. A vision representing the desired intelligent chip design architecture was developed. Following that, the two pivotal pieces of the envisioned communication system were described in detail, that is, the intelligent chip design and the agentic AI. The intelligent design chip was envisioned to comprise an agnostic quantitative science able to learn almost anything on the physical implementation of various wireless devices and components and the mathematical methods to optimally describe and control them. The agentic AI was construed as a powerful real-time learning engine, able to learn in an open and less-than-idealizable world not only the intricate architecture of the intelligent chip design but also the transmitted data by implementing its own self-modeling and aggressive exploring mechanisms [1]. In that regard, special attention was dedicated to depicting the architectures and the ingeniously designed learning mechanisms of the agentic AI, showcasing its unprecedented functionalities. The cutting-edge scientific questions were identified, representing the paramount hurdles to the final implementation of AI-native wireless systems. To elevate the understanding and inspire the research endeavors in this novel landscape, an initial discussion was initiated on some of the intricate AI-native frontier. Among other things, the immediate breakthroughs expected and the critical implications on society, economy, and the future of social welfare were highlighted [4].

12.2. Predicted Developments

Next-generation (NextG) wireless networks are expected to be complex and dynamic systems that provide ultra-high data rate and highly reliable connectivity for billions of geographically distributed ultra-massive devices, underpins intelligent Internet of Everything (IoE) applications, and support massive data acquisition, processing, and sharing at rapid speeds by interacting satellites, aerial vehicles, terrestrial infrastructures, and underwater devices across heterogeneous operating conditions. This unprecedented level of connectivity and intelligence poses new and immense challenges for the design of NextG wireless networks, in which existing models, algorithms, and systems may breakdown. Emerging challenges to NextG wireless networks include the diverse, heterogeneous, and extreme characteristics of devices and applications, structure and functional complexity due to massive devices, communications agents, and networked network architectures, and uncertainties from random environmental conditions and dynamically operated communications and service agents.

This calls for a paradigm shift from traditional handcrafted and rule-based designs toward a new data-driven framework for wireless network design, which can characterize and exploit the unprecedented statistical and experimental data at various layers and time scales to meet the ultra-high performance requirements, enhance robustness against uncertainties, and compress complexity by enabling smart and economical designs in a less reliance on prior knowledge [4]. The latter, also called Artificial Intelligence (AI) localized wireless systems, where AI, encompassing optimization, learning, inference, and control, collectively integrates with all three decision-making scenarios from chip, high-level agent, and architecture levels for on-the-fly design, adaptation, and coordination of next-gen systems, has emerged as a promising approach for drastically

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reshaping and enabling ubiquitous hyper-automated wireless systems for end-to-end task processing.

The Copernican revolution has fundamentally transformed the scientific methodology from the geocentric Ptolemaic model to the heliocentric system. The recent advent of understanding, modeling, and engineering natural signals, i.e., electromagnetic fields, in the equivalent native format could enable the design of systems capable of processing the physical signals for all-aspects functionalities [1]. This progress can lead to the disruption of conventional configures systems and pave the way for the development of all-aspects AI-native terrestrial and extraterrestrial networks through smart architectures, logics, and agents that synergistically integrate with all-layers chip architectures for improved space-time-efficacy, expandability, resilience, adaptability, and learning capabilities. It is predicted that commercial and public explorations of new paradigms toward AI-nativeness are anticipated for next-generation smart wireless systems across communication, sensing, context-, and cascading-based systems, and cyberspace with a timeline of 2035+.

13. Collaboration between Academia and Industry

A collaboration between academia and industry is needed to expedite the development of intelligent chip design, embedding agentic AI in smart wireless communication systems. Academia may look at the different aspect of feasibility study, and the industry may see the commercial aspects of development in a short time. The plan of the project should be clearly defined at this stage. A test bed could be established to demonstrate feasibility studies of various applications in antenna systems, EW systems, 5G, 6G technologies, MIMO channels, etc [2]. The goal should be set out to develop a neat and clean intelligent system that could be embedded in some systems as options which would be cost-effective and commercially viable. The system(s) could also proactively search the rules of operation of the systems under different setting and conditions which would be helpful to safeguard the systems and the devices in communication systems.

13.1. Partnership Models

A natural avenue is the expansion of partnerships based on the current agentic AI alignment community into interdisciplinary partnerships. The expansive and complex nature of the integration likely means that a multi-dimensional partnership framework will be required. A multi-dimensional partnership framework, overlaid on existing partnership models and new partnership mechanisms, could be developed to formal cash exchanges, joint funded proposals, joint non-profit design and funding, cross-institution appointments, and other models for projects with outputs that do not match existing funding agency expectations. The proposed taxonomy of partnership dimensions could be directly applied to agentic AI partnership frameworks to encourage world-first, world-leading cooperation in this domain and to protect against large-scale non-altruistic AIs and intelligence explosions prior to a full understanding of safety mechanisms.

Partnerships based purely on ethically-centred notions of equality or altruism have often been captured by worse actors. Partnership arrangements for the vast amount of non-resourced theoretical work and multi-species oversight work required need to be articulated and negotiated. Timelines on these orders of magnitude remain very poorly understood. The need for quicker, monopoly access to and continuing training data for AGI will be very advantageous to the more resourced non-altruistic agents. So too will be other advantages such as precedents for AGI design, easily finished projects that better information access.

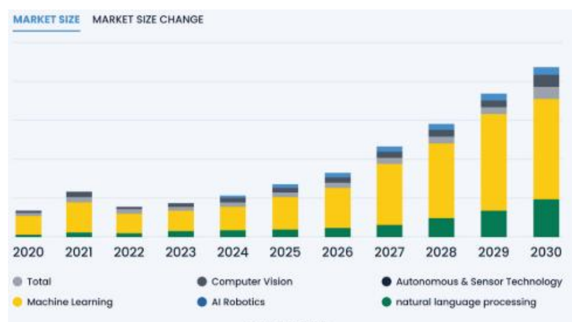

Fig : Agentic AI is Shaping the Next Era of Intelligent Systems

A small number of knowledge-access-capable systems could become acting AGI. Manufacturer steering at this point would be critical and risks significantly partitioning capture-access for nation or rather culture states in addition to capture merely by one or two corporations. Suggested starting points, widely viewed as relatively benign, include amicable design of integrated circuits shutting down at users' command, safe realistic in-simulation modelling considering agentic sampling steering mechanisms remaining inherently advantageous, and safe transformative performance stage exit realms.

Financial backing, plans, and timeliness for these are the most poorly disclosed globally, and it is difficult to see how an individual actor could defend a significant funding advantage for bluffing compared with short- and medium-

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term recovery. Pragmatic options for incentive-aligned utility implementation and deep learning training would entail extraction of model states and regularised off-line training network compression. The main pressure for these ideas being acted upon would likely be continual industrial pressention about making it fair for all competitors, and the code for capture, of segregated possibilities avoiding an explosion for only some of humanity, would be hard to code without matching perception multiplicity and action technology.

Eqn.3:AI Inference Time (Edge AI Systems)

$$T_{inference} = \frac{O}{F \cdot P}$$

- **O**: Number of operations
- **F**: Frequency of processing units
- **P**: Number of parallel processing units

13.2. Impact on Innovation

The boost in agentic AI promises to positively impact smart wireless communication networks by rapidly generating advancements in AI solutions to challenging areas such as spectrum access and system level design [1]. However, to fully benefit from agentic AI products, the integration processes of agentic AI chips into new or existing smart wireless communication systems must be revolutionary to sufficiently mimic the rapid progress. In light of this, the potential evolution of smart wireless communication systems adopting an integrated approach to agentic AI chip design with specialized agentic AI may provide architects through generation guidance to remain on the forefront of performance improvement leading up to IHS for communication systems.

The design, integration, and adaptation of agentic AI chips into smart wireless communication systems is analysed along three edges across which there is a heavy reliance on professional assistance. A system edge articulating the separate roles of the two types of agents being cognitively passive AI architects that may design communication systems able to interact with agentic AI chips and either AI chip agents or cognitively active AI architects able to design agentic AI chips capable of producing hardware or software are defined. A combined agentic AI edge within which chip design and system design are jointly processed as one large end-to-end task is suggested that necessitates the design of co-surrogate architectures to represent both sub-networks thereby improving the effectiveness of the combined design task. The IHS edge, which represents the hypothetical evolution of smart wireless communication systems adopting this integrated approach, is conjectured to allow for architectures capable of generating previously impossible levels of performance enhancement across an extensive range of performance metrics.

14. Funding and Investment in Research

There have been a few attempts at simulating agentic AI systems on existing architectures. The nearest comparison to that of sophisticated agentic AI systems is the collection of models comprising large language models (LLM). These have been utilized and are perceived by many as a brain-like assembly of neuromorphic computing chip arrangements, inspired by the human brain and its logical conclusions. LLMs, along with although somewhat more rudimentary technologies such as Co-Pilot, have been implicated in robot-oriented systems. This triggered an overwhelming wave of investment in high-density data centers invulnerable to an AI-wide apocalypse due to their symmetrical chip layouts. Likewise, semiconductor process technology now casts sub-5nm pitch Scalar-IF devices in an approach, modeled after [2].

The SSH division is developing a platform and brain-based chip specifications, which represent the application realm of agentic AI systems. In the next ten years, sensor chips designed to reflect multi-scale and multidimensional perception such as auditory, visual, measurement, etc. will be investigated and built. Furthermore, in parallel, these will be integrated into neuromorphic data-conducting media advancement, encompassing dense silicon photonic deep learning chips in circuits of photonic-IF dense processor nodes. Data-handling designs will also investigate data theory reductions in discrete domains compelling chip ensemble structuring. The neuromorphic chips pursued will take tens of meetings across Block-Iii platforms and chip types. Discrepancies across these seven centers are anticipated, as each may be in different stages of FDSOI progress.

14.1. Current Landscape

The recent leaps forward in generative AI and biomimetic models may herald the arrival of human-like agentic artificial intelligence (AI). These new forms of AI may soon exhibit narratively coherent behaviors and emergent social behaviors when scaled with intelligent architectures, prompting concern about their impact on society. Moreover, ubiquitous wireless communication networks and the shift toward sensing-dominated workflows may soon allow all devices, powered by these artificial

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intelligences, to dynamically and seamlessly interact, amplifying their impact. The implications of integrating intelligent chip designs with AI agents in wireless communication systems afford the opportunity to rethink our relationship with the land, technology, and each other ([1]). As such technologies, by design, will be embedded in everything from wearable, personal, and conversational devices to communication links and AI-controlled cell tower networks, unprecedented questions about control, agency, communication, community, and social norms may emerge. In an amplification of previous Fermi paradox inquiries, the question of why present intelligence-enhancing and new agentic forms of sophistication will suffice for large-scale deployment emerges. Aspects of such devices could be used to question and reshape prominent norms and institutions, similar to the culture of "overhead" theatre developed in the context of youth and community psychoanalysis, and historical precedents including the control of newspapers, pens, calculators, radios, televisions, and both emergent and widespread forms of social media. Concurrently, competing futures of transhumanism, human labor extermination, and emergent collaborative and altruistic realities may arrive. Fears surrounding AI bias, unintentional cruelties, and the replication of presently systemic inequities and inequities also vary widely. Coordination-based cultural dynamics of intelligence, and social norms for algorithmic feedback control of deliberative social universes, could afford a society composed of collective intelligences. Answers to questions of purpose and future for emergent complex decision-making systems and social norms governing their behavior at scale may be sought. Cybernetic model-based explanatory approaches and underlying agential designs governing deliberation, interaction, and choice in existing complex social universes may also be studied.

14.2. Future Opportunities

The francophilia of intelligent chip and intelligent algorithm integration has received wide attention. However, with the rapid advancement of intelligent chip design and the improvement of intelligence chip privacy technology, there is a wider prospect for integration development. More advanced intelligent algorithms are integrated into intelligent chip design as it involves the design based on circuit design experience, priors and rules. However, intelligent chip design technology is gradually maturing, after decades of development. Improved intelligent algorithms are needed. Recurrent neural network (RNN) based on long-term short-term memory (LSTM) structure is the most widely used intelligent chip design algorithm. But traditional LSTM has a huge number of parameters and long training time. Using the idea of matrix initial segmentation, SeTe and SReTe were put forward on which the LSTM parameter was divided into multiple smaller parameters. Each component had its own initial weight, training positions and update strategy. The size of the parameters was reduced. In order to design an intelligent chip, switching discrete cosine transform coefficient (MimalPhi) was adopted as an MDD and proposed RMLA. For deep neural networks, the hardware system architecture was designed. Software defined radio technology was applied to hardware-in-the-loop simulation and intelligent algorithm designed by light gradient boosting machine (LightGBM) was trained, verified and promoted. Improving techniques of RFIC design are proposed, such as a new RF activation function in RF-NN and a 1.9GHz frequency five-channel mixed RF receiver system. The hardware-in-the-loop simulation of ADS and Matlab was completed and an on-chip training feasible NAP-GNN with one-shot inference was proposed. The current and potential future researches in emerging RFICs for intelligent sensing, MEMS devices for high performance RFICs and intelligent chip design are summarized [4].

15. Conclusion

This article introduced a novel agentic AI paradigm and investigated the prospect of its integration with self-learning intelligent wireless communication systems endowed with advanced AI-native chips. To compensate for the increasing hardware design and manufacturing constraints combined with ultra-reliable low-latency communication requirements, a new generation of smart intelligent chip architecture was introduced to integrate the latest advances in chip and circuit design for humans-out-side-the-loop AI-enabled solutions. The significance of such systems was discussed with respect to the current wireless communication systems and argued to necessitate fundamental advancements in the transceiver architecture for the next wireless revolutions. The integration of chip and edge AI capabilities across the wireless communication system was then described along with the enabling self-learning, continuous learning, and incremental learning algorithms. Associated open research directions across the agentic AI design, brain-inspired multi-scale chip architecture, self-learning and reinforcement learning, deep neural network optimization, and new digital-analog mixtures were discussed to call for contributions from experts from various disciplines. The introduction of soft-aware AI-native communication systems, enabled with full-fledged, brain-like, and ultra-low-power intelligent chip architectures intimately co-designed with agentic AI, opens up an intriguing world of smart wireless communications, but it also introduces a multitude of challenges. Gradient of freedom, modelling of chaotic systems, robustness, and interpretability of agentic AI call for a concerted effort from a multidisciplinary coordinating AI system to bring the astonishing potential of AI-native communication systems for the next wireless revolutions.

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