



AI Agents for Semiconductor-Enabled 6G Networks

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Abstract

Next-generation telecommunications are increasingly overlapping with various application domains, most notably vehicular systems, the Internet of Things, augmented and virtual reality, and robotic swarms. These overlaps underpin the need for different levels of autonomous operation—from the user perspective—while posing unique challenges for the underlying communications systems, which must still meet the operational objectives of each individual domain. Suggested solutions exploit advancements spanning mobile networks, cloud-edge computing infrastructures, algorithms for wireless resource allocation, and the full automation of system operations. Within this context, agentic AI alters the traditional separation of aircraft control planes—mainly dedicated to perception, planning, and acting—by integrating the development of sufficient high-fidelity capability. High levels of task automation supersede human engagement and enable system stewardship, provided the AI are developed, deployed, and managed under appropriate principles.

Even so, support for most domain requirements remains oversimplified, with operator assistance and resource provisioning and allocation invariably under human skill. Consequently, a new layer of cognitive automation spanning perception, decision making, and operation is being gradually integrated into systems via AI dedicated to such tasks. The framework governs a self-aware general-purpose cognitive loop that officiates the request and supply of contextualized information and control actions within the context of data acquisition and potentially also for planning and learning adopted by lower-level AI. Because its candidates reside within the operational ecosystem and their autonomy level can also vary from system supervision to collaborative support, the cognitive loop naturally lends itself to agentic AI. Beyond theoretical considerations, the approach has been applied to the dynamic scheduling of integrated sensing and communications resources.

Keywords : Agentic AI; cyber-physical systems; sixth generation networks; resource allocation; reinforcement learning; multi-agent systems; causal inference.

1. Introduction

Next-generation telecommunication networks must fulfill ever-increasing demands while balancing conflicting user requirements. These opposing considerations complicate the design of systems that allocate resources autonomously. Highlights of prior work include investigation of agentic AI-based management control for resource allocation in semiconductor-enabled 6G infrastructures. New technologies should extend the traditional perception-decision-action control loop into the cognitive domain,

opening up opportunities for novel data-sensing sources and formulation of agentic resource-allocation problems.

The concept of agents extends Liu's definition to include the autonomy level. The degree of autonomy is determined by the winner of the decision-making process, which can be a human, a machine, or a hybrid combination. The ultimate objective of agent-based decision-making should be to minimize the network management overhead while maintaining sufficient performance requirements. Such agents could be combined with Liu's control loops to create

assurance agents for agentic resource allocation in wireless networks.

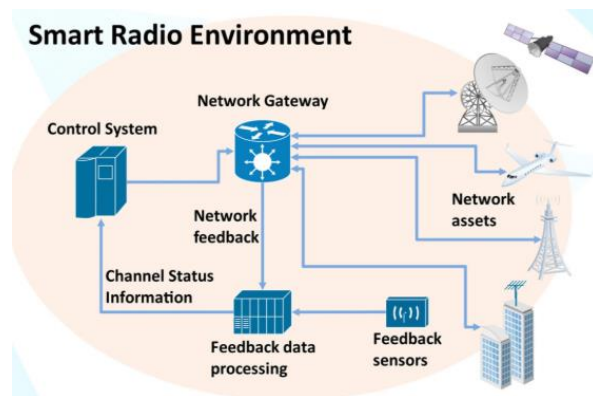


Fig 1: 6G Wireless Communications and Artificial Intelligence

1.1. Background and Significance

Telecommunication technology advances, artificial intelligence (AI) and machine learning (ML) algorithms become integrated into various aspects of future networks, and cloud-enabled development resources boost the provision of non-telecommunication services by telecommunications operators. Autonomous agents are expected to operate in these factories, making important decisions and allowing for complex task execution. Their introduction to communication networks, particularly in resource allocation tasks, allows a broad conception of agentic AI in Next Generation Networks (NGN). This paper explores the application of agentic AI in the context of wireless resource allocation for semi-conductor enabled telecommunications networks from a hybrid research design perspective. Hybrid designs encompass elements of both traditional and advanced internet-based models. In the context of resource allocation for integrated cellular, wireless-local-area, and wireless-sensor networks, Hybrid designs have been limited to the low level of a single decision maker.

Fundamentally, Agentic AI relates to the deployment of agentic and autonomous AI Agents. A complete definition of Agentic AI must consider the levels of autonomy and agentic development of the autonomous decision makers. If the decision makers are at a low level of agentic development with a limited level of autonomy, it may be more appropriate to conceptualise the allocation tasks as Agent-Led AI Tasks. In this complete definition, Agentic AI refers to tasks executed by agents operating at any level of autonomy and Agent-Led AI Tasks refer to jobs executed by agents with a low level of agentic development and autonomy.

1.2. Research design

Although AI is widely believed to deliver fully autonomous operation without the need for human intervention, a more extensive analysis indicates that this is unrealistic. The problem of defining the correct level of autonomy for intelligent agents is key, with maximization of autonomy not necessarily desirable. Intelligence can help in delegating low-level tasks or those that require fast reactions to agents, thereby freeing humans to deal with more complicated issues. Human involvement remains important for final decision-making and cannot be completely eliminated, but it can be minimized while still retaining a human-in-the-loop approach. Autonomy is typically divided into four levels—no autonomy, decision aides, decision support, and decision automation—with the granularity increased by considering who decides.

Moving down the levels from no autonomy, AI agents could be used to define policies governing network operation, while humans would remain responsible for high-level strategy. Below the decision support level, the quality, speed, and volume of decisions could be increased by using intelligent agents as the decision makers. The key area of research is defining the correct balance for this middle level of autonomy where AI makes key decisions such as wireless resource allocation, while humans retain the supreme control.



Equation 1: Wireless link quality (SINR) → rate/QoS primitives

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Step 1: Define SINR

For a user u served by base station b on a resource block (RB) k :

$$\text{SINR}_{u,k} = \frac{P_{b,k} |h_{b \rightarrow u,k}|^2}{\sum_{b' \neq b} P_{b',k} |h_{b' \rightarrow u,k}|^2 + N_0 B_k}$$

Where

- $P_{b,k}$: transmit power allocated by b on RB k
- $h_{b \rightarrow u,k}$: complex channel gain from b to u on RB k
- interference sums other cells b'
- N_0 : noise power spectral density, B_k : RB bandwidth

Step 2: Convert SINR to achievable rate (Shannon form)

$$R_{u,k} = B_k \log_2 (1 + \text{SINR}_{u,k})$$

Step 3: QoS constraints often use rate or delay

A typical QoS constraint:

$$\sum_k x_{u,k} R_{u,k} \geq R_u^{\min}$$

where $x_{u,k} \in \{0,1\}$ indicates whether RB k is assigned to user u .

This “rate from SINR” chain is what lets you map **context sensing** → **scheduling decision** → **reward** in RL.

2. Theoretical Foundations of Agentic Resource Allocation

Agentic resource allocation for next-generation telecommunications combines agentic AI—AI that generates, directs, acts on, and interprets its own goals and decisions—with dynamic scheduling, multi-agent coordination, causal inference, counterfactual reasoning, and explainability-specific measures. The novel allocation mechanism aims at maximizing network performance and user quality of experience while maintaining low service latency, preventing excess hardware wear, and managing data privacy. The cognition loop is divided into perception, decision-making, and action phases, each with specific functional requirements.

Agentic AI entails decision-making without human intervention. Updates to the AI's cognition loops are confirmed by a human—specifically, the decision-winning element of the allocation problem. A network agent's decisions may affect other network elements, which in turn affect the agent's operations. Consequently, network governance, rules for the allocation, and ethical considerations of the agentic AI can be embedded directly into the network's structure.

2.1. Agentic AI and Autonomy in Network Control

Four levels of autonomy characterize different operation paradigms—fully manually controlled, fully autonomously controlled, periodic human supervision, and fully automatic with no human intervention. The choice depends on the decision level, either tactical involvement of humans (e.g., Mission Planning or Coordination and Task Allocation) or strategic management (e.g., Workpackage Development and Resource Allocation). Human decision-makers prevail at the management level, deploying control actions, regulations, and policy setups to support network service provisioning. Tactical decisions, involving the joints of human operators and AI algorithms, allocate mission-level resources such as spectrum and computing.



The cognitive AI logic determines whether AI algorithms or humans are best placed to govern and oversee control loops with subtle dynamics by analyzing data and information from lower modules. The final decision-taking at the governance and strategy level is shared between humans and AI. Carrying over the ALFUS concept, network services executed by these application-driven AI agents should be explainable—i.e., the elements of a decision process should be identified in natural language and described in a coherent way for the agent actions to be seen, understood, and trusted by users.

2.2. Wireless Resource Allocation Fundamentals

Wireless resource allocation encompasses a set of features and functionalities spanning: (i) spectrum allocation, including routing and power control; (ii) resource scheduling, which determines when and for how long devices transmit; (iii) management of quality-of-service (QoS) requirements; (iv) interference management across a range of radio lines; and (v) performance evaluation through multiple success and failure metrics. For semantically-centric and agentic AI-driven control in semiconductor-enabled 6G environments, the integration of these features across device and network capabilities and the solutions implemented in their action and decision-making systems hold particular significance. Such consideration offers a natural grouping of the semantic structure in 6G resource allocation capabilities into the three subsystems for wireless technologies: sensing, storing, and acting.

Guaranteeing logical relevance and consistency with this dependency-driven approach enables the specification of a multi-layer cognitive loop, without loss of generality, for dynamic scheduling formulation based on reinforcement learning techniques. A learning-to-learn capability further enables the integration of contextual information into the optimization of resource allocation and management, responding dynamically not only to the changing characteristics of the allocation environment or dataset but also to updating operational objectives, constraints, and viability. Multi-agent or game-theoretic cooperation and coordination elements supplement the standalone aspects of

the systems and encapsulate the completeness of operation and team reasoning or defence strategies required for practical deployment in any threat model.

Equation 2: Dynamic scheduling as an optimization objective (dropped packets)

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Step 1: Queue evolution

Let $Q_u(t)$ be queue length (packets) for user u at slot t . Let arrivals be $A_u(t)$, served packets be $S_u(t)$, and dropped packets be $D_u(t)$ (e.g., due to buffer overflow or deadline expiry).

A standard queue update:

$$Q_u(t+1) = \max\{Q_u(t) - S_u(t), 0\} + A_u(t) - D_u(t)$$

Step 2: Scheduling decision influences service $S_u(t)$

If user u is scheduled and gets rate $R_u(t)$, then served packets:

$$S_u(t) = \left\lfloor \frac{R_u(t) \Delta t}{L} \right\rfloor$$

(L =bits per packet, Δt =slot duration)

Step 3: Optimization statement (conceptual)

A common formulation:

$$\min_{\{\text{allocations}\}} \mathbb{E} \left[\sum_t \sum_u D_u(t) \right] \text{ s.t. QoS/power/bandwidth constraints}$$

This is the objective RL replaces with **reward maximization**.

2.3. Semiconductor-Enabled 6G Network Infrastructure

Silicon photonic hardware accelerators for MIMO

processing and optical backplane deployments simplify scaling the associated network control traffic. Photonic mesh fabrics provide the very high-bandwidth and extremely fine-grained spectrum slice switching needed between multiple bands. Monolithically integrated RF-PMA fabrics, with capacity extensible by die stacking through vertical interconnect access, support densely packed, chip-scale radio frequency transceivers and high-capacity carrier frequency overlaid wireless links across all bands simultaneously. In-network acceleration architectures deploy programmable miniaturised processors directly on the transmission path for mobile-cloud-sensing-communication edge compute placement. Integrated communication-radar RF-PMAs allow ultra-wideband joint sensing-communication systems using the same transmission resources, addressing resource management for both services from a single location within the control hierarchies.

Resilience and sustainability of these technologies return to standardisation, with the physical and network layers uniquely covered by NGS-DGN standards. Decision models and GPT training methods, driven by Terahertz testbed data, assist empowerment of CSP-operated networks, creating local market opportunities outside the CSP domain, thus broadening base investment/reward ratio issues. The development of economic models, methods, procedures, and analysis techniques for autonomous decision-making across all technologies creates open source requirements and priorities for an open ecosystem.

3. System Architecture and Cognitive Loop

The system architecture incorporates a cognitive loop spanning sensing, decision-making, and action, enabling ongoing adaptation through semiconductor-enabled resources. Sensing data from radio, network, and environmental sensors serve to understand operational environments. Network control objectives comprise wireless resource adaptation—spectrum, scheduling, beam positions—and enhancement of context and mobility

models. Decision-making combines Reinforcement Learning for scheduling and resource adjustment budgets, Multi-Agent Coordination for conflict resolution, and Counterfactual Causal Inference for transparency. The action phase executes control actions on network resources while using latency-sensitive information to adapt allocation within practical reconfiguration timeframes.

Cognitive information sensing integrates data from multiple sources to enhance contextual understanding of environments and mobility patterns. Sources include radio sensors such as the Received Signal Strength Indicator (RSSI)/Location of Signal Source (LSSS) for proximity and direction of users; antennas for spatial diversity; network emulators for interference and load; and external sources for road traffic. Context data fusion enables sub-area mobility predictions via recurrent neural networks (RNNs) with user location history, positioning of base stations for text state transition, Patterns of Life (PoL) learnt from user mobility data, and changes in road traffic patterns. Awareness of factors such as outdoor-inrail environment assists in selecting traffic and channel models and adjusts parameters such as signal-to-interference-plus-noise ratio (SINR) and severity for reliability.

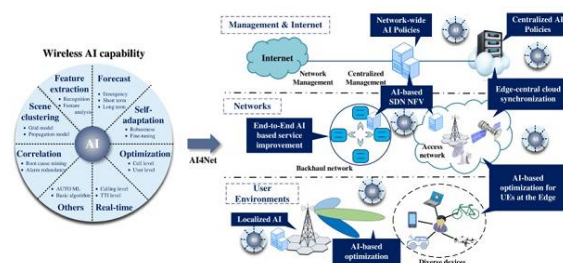


Fig 2: The Convergence of Intelligence and Connectivity

3.1. Perception: Sensing and Contextual Information

Distributed intelligence relies on information from diverse sources. Sensor networks monitor environmental aspects



such as temperature, humidity, air quality, and location. Context models classify events and describe user activity, mobility patterns, and surrounding devices. Support communication for disaster management and environmental quality prediction and control.

Situational awareness enables prediction of future network conditions to improve service delivery. Mobility patterns of connected users and devices are also predicted for proactive steering of ongoing communications. Cyber-physical integration promotes real-time awareness of space, aiding the establishment and provision of high-quality connections. AI-enabled intra- and inter-network data fusion exploits observations from several sources. A central function maintains context information, while network cloud points store large databases.

3.2. Decision-Ming: Policy and Optimization Frameworks

Wireless resource allocation encompasses various interrelated functions, including spectrum allocation, service scheduling, QoS satisfaction, interference control, and power, beamforming, and transmission-control optimization. Cognitive AI enables more automated executive-level decision-making. For challenges amenable to single-shot solutions, the decision-making block implements a control policy, such as for resource slicing or dynamic power allocation. The policy can either be a lookup table for reinforcement learning or a pre-learned mapping from context features to allocation parameters. A policy update is triggered whenever the operational context undergoes a significant change, for example, on major shifts in service-demand patterns.

In contrast, multiple-instrument resource-allocation problems are addressed with multi-layer optimization. The decision-making block first selects appropriate objectives and constraints for the RPGA reinforcement-learning agent. Combined learning-planning controllers, which leverage the predictive capabilities of a context-aware model, are the preferred solution. The inferred implicit or explicit context is then used to tune the allocation sub-components, such as

defining couples of temporary equilibrium models of commingling capacity or guiding performance-driven path-steering and placement of distributed-predictive algorithms.

3.3. Action: Resource Adjustment and Network Adaptation

Control actions are carried out by adjusting the resources allocated to infrastructures. The network state observed through context-aware sensing provides feedback to validate the utility derived from the previous plan. Kinetic agents acknowledge the decreasing utility associated with rapidly changing environments and consider motion patterns of users, service requests, and serving infrastructures to reduce feedback latency.

Connecting PMA fabrics introduces intrinsic reconfiguration latency budgets. The communication EM envelope realises the high-dimensional parallelism of elementary reconfigurable wireless units, raising a plethora of simple yet effective actions. Beyond communication EM waves, the sensor EM envelope generates twice the alleviation of the terminal throughput at the same resource cycle. The joint allocation procedure determines the selected action and reconfiguration procedure. Handling PMA fabrics as circuit-like engine resources extensively supports artificial agents' telecontrol objectives. Reconfigured chip-scale radios embedded in circuit-really are adjusted to shape the active communication EM envelope prescribed by control agents. The temporal control loop latencies, which represent the budget for completing action adjustments and receive feedback signals, are expected to remain lower than the K connectivity round latch.

Equation 3: RL scheduling formulation (MDP) and full step-by-step equations

1 Define the MDP ingredients

State

$$S_t = \text{concat}(\text{queues } Q_u(t), \text{ SINR stats, load, mobility/context})$$



Action

a_t = (choose “winner(s)” / allocate RBs/power/beam/slice)

This matches the paper’s “selecting winners” language

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Reward

To minimize drops and delay, define reward as negative penalties:

$$r_t = -\alpha \sum_u D_u(t) - \beta \sum_u Q_u(t) - \lambda (\text{power or reconfig cost})$$

This directly matches the paper’s “minimizing dropped packets” but expressed as reward maximization

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Return

$$G_t = \sum_{i=0}^{\infty} \gamma^i r_{t+i}, 0 \leq \gamma < 1$$

State-value

$$V^\pi(s) = \mathbb{E}_\pi[G_t \mid s_t = s]$$

Action-value

$$Q^\pi(s, a) = \mathbb{E}_\pi[G_t \mid s_t = s, a_t = a]$$

Start from definition:

$$Q^\pi(s, a) = \mathbb{E}_\pi[r_t + \gamma G_{t+1} \mid s_t = s, a_t = a]$$

But G_{t+1} under policy π equals $V^\pi(s_{t+1})$:

$$Q^\pi(s, a) = \mathbb{E}[r_t + \gamma V^\pi(s_{t+1}) \mid s_t = s, a_t = a]$$

And

$$V^\pi(s_{t+1}) = \mathbb{E}_{a' \sim \pi(\cdot \mid s_{t+1})}[Q^\pi(s_{t+1}, a')]$$

So:

$$Q^\pi(s, a) = \mathbb{E}[r_t + \gamma \mathbb{E}_{a' \sim \pi}[Q^\pi(s_{t+1}, a')]]$$

We want optimal $Q^*(s, a)$ satisfying Bellman optimality:

$$Q^*(s, a) = \mathbb{E}\left[r_t + \gamma \max_{a'} Q^*(s_{t+1}, a')\right]$$

Q-learning approximates this fixed point by stochastic updates:

1. Observe transition (s_t, a_t, r_t, s_{t+1})
2. From TD target:

$$y_t = r_t + \gamma \max_{a'} Q(s_{t+1}, a')$$

3. TD error:

$$\delta_t = y_t - Q(s_t, a_t)$$

4. Update:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta \delta_t$$

where η is the learning rate.

This is the canonical “trial and error” policy learning the paper describes

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4. Algorithms for Resource Allocation



Wireless resource allocation in next-generation networks is a promising area of human-centric agentic AI support, with research focused on dynamic scheduling, near-real-time allocation by multiple non-learning agents, and causal inference to ensure transparent decision-making. Dynamic scheduling formulations focus on quality-of-service conditions and are aimed at minimizing the volume of dropped packets. A reinforcement-learning-based approach enables agents to learn the optimal scheduling policy by maximizing the reward signal, verifying the concept through simulation results that confirm convergence. To balance exploration and sample complexity, an exploration probability dependent on the total number of sampled episodes is proposed. The near-real-time scheduling scheme uses multiple agents, learns from past scheduling episodes, and does not rely on centralized knowledge of link states.

Multiple agents autonomously allocate budgeted communications resources using coordination protocols. The communications resource allocation process is modeled as a two-sided market, with resource owners forming coalitions and resource consumers executing a bargaining process. The communication protocols are capable of dynamically addressing the coalition-formation and conflict-resolution processes, enabling the agents to quickly adapt to non-convenient changes within the network. The causal inference and explanation approach establishes a causal model predicting the number of dropped packets in a wireless system and enables counterfactual analyses of resource allocations. By incorporating the response structure of the conditional outcome distributions, agents provide transparent explanations for their decisions, allowing third parties to analyze and evaluate the correctness of the allocations.

4.1. Reinforcement Learning for Dynamic Scheduling

The scheduling of wireless resources is decomposed into an agent-based reinforcement learning (RL) problem. Each scheduling entity determines its own allocation policy by interacting with the operation environment via trial and error. The scheduling entities collaboratively and complementarily perform scheduling tasks by selecting winners, with incentives embedded in the reward definition.

Such a scheme significantly alleviates the burden of centralized coordination and control. Extensive theoretical analysis guarantees convergence of the learning process, provides a unified view of exploration strategies, and establishes sample complexity in a multi-agent setting. These results pave the way for the practical use of RL in dynamic and heterogeneous scheduling scenarios.

The learning process can be formulated as a multi-agent reinforcement learning problem with decentralized training and centralized execution. The scheduling needs of all resources are combined into a single task by organizing scheduling entities into an N-dimensional space, where each dimension corresponds to a resource. The success of each scheduling will trigger a reward determined by the expected reward function. The resulting reward function has a built-in incentive mechanism as long as the winner of the scheduling is not strictly isolated. The reward structure provides an explanation of how exploration strategies, such as decaying ϵ -greedy and Boltzmann, influence the decision-making process.

4.2. Multi-Agent Coordination and Negotiation

Wired and wireless scheduling problems are often formulated as single-agent optimization tasks with the corresponding policies generating the required control actions. As the number of agents in a network increases, however, multi-agent interaction becomes the predominant factor. Learning by imitation, social learning, or multimodal approaches discover how agents coordinate in a network to make optimal decisions. In multi-user communications systems, cooperation capabilities among users exist at several levels. At the lowest level, user agents coordinate by using a common radio resource allocation policy that can either be broadcast or shared. At the next higher level, user agents form small coalitions to jointly determine optimal actions such as transmit power, scheduling, or beamforming. If agents are rational decision makers, the agents in each coalition can self-organize or form dynamically formed coalitions based on either bargaining or game-theoretic frameworks. Coalition formation naturally extends to larger groups of multiple coalitions.



Conflict resolution among agents is another important area. Multi-agent conflicts may arise when agents have incompatible objectives and the resources are insufficient to satisfy each user's minimum QoS level. Current methods include bidding, voting, barter mechanisms, and Markov models with the resource automatically allocated according to a decision maker, authority, or fast agent with a small feedback delay. Negotiation requires agents to exchange messages, seek mutual agreement, and reach consensus on a joint decision while minimizing the negotiation effort within a given time limit. Recent advances provide an agenda-based model to enhance collaboration with an organized negotiation framework and the acceptance of ideas from other agents. It combines coordination with a consensus-based approach that can bring about agreement without operating on a shared agenda.

4.3. Causal Inference and Explainability in Allocation Decisions

The causal relations affecting the system dynamics and the context-dependent allocation decisions should be identified, modelled, and used for interpretability and require special attention to allow for pre-emptive resource planning actions. Causal inference provides a framework for discovering causal relationships from observational data and performing counterfactual reasoning through do-calculus. Data-driven causal models can be used to identify the most significant features affecting decisions, to uncover hidden structures, to assess the robustness of the learned policies, and to evaluate the impact of future events on resource management. The interdependence of causal reasoning and reinforcement learning can be exploited to enhance the training process by incorporating counterfactual data during exploration and to increase the interpretability of learned policies. Like other ML and AI-based resource management approaches, the causal analysis requires transparency and auditability of allocation decisions for the stakeholders and the built environment.

The reduction of the number of exploitable states, actions, and rewards improves the sample complexity of reinforcement learning. Consequently, the explainability of

the systems can be increased through the introduction of causal inference for studying the influence of context on expected actions, rewards, and agents' behaviours and for producing explanatory models and interpretable states through counterfactual analysis. A causality-driven architecture defines the state space in terms of contextual features that are expectable functions of the past and present, captures causal interactions through a probabilistic causal graph, and identifies the set of exploitable contextual factors by adopting a context-modulated governance structure. The context-adaptive model provides an interpretable multi-scale representation of the agents' behaviours by merging elements of reaction-based, situation-aware, and decision-theoretic multi-agent systems.

Equation 4: Exploration strategies derived

4.1 Decaying ϵ -greedy (paper mentions it)

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Policy definition

$$\pi(a | s) = \begin{cases} 1 - \epsilon_t + \frac{\epsilon_t}{|\mathcal{A}|}, & a = \arg \max_{a'} Q(s, a') \\ \frac{\epsilon_t}{|\mathcal{A}|}, & \text{otherwise} \end{cases}$$

A standard decay schedule (one of many valid choices):

$$\epsilon_t = \epsilon_{\min} + (\epsilon_0 - \epsilon_{\min})e^{-kt}$$

This matches the paper's "exploration probability dependent on the number of sampled episodes"

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4.2 Boltzmann / softmax exploration (paper mentions it)

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$$\pi(a | s) = \frac{\exp(Q(s, a)/\tau)}{\sum_{a'} \exp(Q(s, a')/\tau)}$$

- If $\tau \rightarrow \infty$: nearly uniform random
- If $\tau \rightarrow 0$: nearly greedy argmax

5. Semiconductor-Enabled 6G Network Technologies

A wide range of technological advances will characterize semiconductor-enabled 6G networks. The available spectral resources will be flexibly managed by employing advanced modulation and coding schemes, as well as spectrum-slicing capabilities optimized in real time. The availability of high-performance solid-state hardware accelerators will make it possible to integrate approximate computing or sensing and communication tasks. The extension of the air interface with sensing capabilities will support novel integrated sensing-communication frameworks ensuring sufficient sensing quality and minimizing cross-domain interference. The introduction of edge computing systems for low-latency services will be complemented by effective in-network acceleration.

Modulation and Coding: Successful exploitation of the wireless medium relies on appropriate modulation and coding schemes. They must fulfill a number of requirements: Joint detection and decoding in multi-dimensional space; Different MCS at transmitter and receiver; Adaptive modulation and coding for efficient spectrum management. Spectrum channels with an FDM structure must be supported. For applications with an inherent delay constraint, spectrum slicing is a solution. A combination of long-term planning and short-term dynamic adaption, respectively of dedicated and adaptive Spectrum Management, is envisaged.

Integrated Sensing and Communications: The realization of joint sensing-communication frameworks represents an intriguing research trend. Waves used for data signal transmission can, in principle, be co-opted for sensing purposes, too. The scenario faces the challenge of realizing a satisfactory level of sensing accuracy while avoiding or

mitigating any interference on the joint channel. Edge Computing and In-Network Acceleration: Deferring the execution of services to a cloud located far from the end users has intrinsic disadvantages for delay-sensitive applications. A natural and current solution is represented by edge computing. Such architectures enable lower latency and enhanced quality by pushing the computing resources toward the edge of the network. End users can access low-latency computation either via a placement optimization that determines the location of the computing resources.

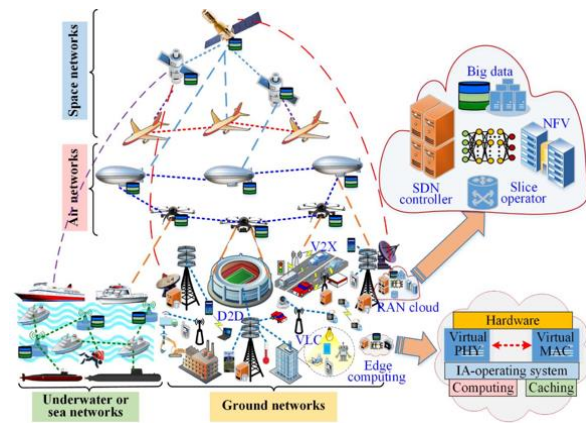


Fig 3: Semiconductor-Enabled 6G Network Technologies

5.1. Advanced Modulation, Coding, and Spectrum Management

Advanced modulation and coding schemes, coupled with dynamic spectrum management, are crucial to support the rich diversity of services blurring the distinctions between wireless and wired systems in next-generation telecommunications. To fully leverage the advantages of frequency-selective channels, adaptive modulation and coding (AMC) schemes are needed, with modulation order and detection methods adjusted based on channel quality information. Additionally, resource allocation strategies should incorporate channel capacity to maximize throughput and minimize transmission delay. Seamlessly integrating channel estimation with parameters of system components—



such as modulation order, transmission power, and transmit/receive antennas—increases channel capacity comparison accuracy.

Spectrum slicing and dynamic spectrum management enable a flexible deployment of 6G services. Composed of heterogeneous frequency bands, these methods can satisfy the specific requirements on channel width, latency, and quality of service (QoS) of advanced services and improve overall spectrum efficiency. A deep reinforcement learning approach enables dynamic adaptation of the available frequency bands and power control for various devices while minimizing interference. On the other hand, dynamic self-optimization of resource allocation in orthogonal frequency division multiplexing systems enhances efficiency under certain QoS constraints and employs sub-carrier and bit allocation with adaptive power control.

5.2. Integrated Sensing and Communications

Conventional communication systems achieve radio-wave sensing and localization using dedicated hardware. Conversely, ISAC systems, while transmitting information, simultaneously capture and process signals reflected by nearby objects to infer surrounding information, paving the way for unattainable functionalities for conventional systems, such as transmit beacons on the communication link. Although ISAC systems, by integrating sensing and communication, capitalize on a common wireless channel, they do introduce significant obstacles.

Sensing and communications are physically coupled and have conflicting requirements. Hence, resolution of these increases the demand for interpretation algorithms and hardware designers. Real-time scenario exploration requires the computing capability for properly interpreting the data. The computing layer not only needs to be geographically and temporally distributed to decrease all the introduced latencies but also needs to possess high computing capability. Subsequently, the integration of ISAC nodes in the current networks needs to consider how ISAC functionalities can be operated without degrading the service provision of the communication links. Marginal decreased

accuracy with the increased distance (in terms of time-of-flight) could be acceptable if guarantees of a novel communication service are provided.

5.3. Edge Computing and In-Network Acceleration

Advancements in semiconductor technologies enable the integration of large chip architectures and associated high-performance hardware accelerators at the radio edge of network infrastructure, where resource demands often peak because of high user densities. The positioning of these components in close proximity to the wireless-user equipment allows for placing fast-inference AI-based data processing functions that ameliorate latency-sensitive applications without the costly round trips to cloud-service data centers. Thus, proper placement of application workloads is crucial to meet the low-latency requirements for real-time communication and for properly exploiting the processing capabilities of the radio-edge hardware accelerators.

These include traditional enhancement components, such as cloudlets, as well as other layer-on-top or layer-besides functionalities that help improve latency-sensitive data traffic while guaranteeing deployment feasibility, avoiding the emergence of new bottlenecks. Additionally, the diversity of artificial-intelligent-on-the-edge services enables intelligent “in-network acceleration” functions that provide timely-enhanced in-sequence delivery of data by anticipating imminent network congestion, improving quality-of-service levels employed in various applications. Control for network-wide latency minimization is key to avoiding the emergence of new bottlenecks in the supply chain, so dynamic resource-supply information across the interactive supply chain of low-latency services becomes decisive to properly operate classic and overlaid functions without jeopardizing the low-latency integrity of such services.

6. Security, Privacy, and Trust in Agentic Allocation



Robust wireless resource allocation requires trust in the controlling agents and the decisions taken. However, a higher level of autonomy exposes greater surfaces for adversarial attacks. This area is usually neglected in the agentic paradigm but is crucial in sensitive areas like health, military, or transport. Addressing security, privacy, and trust in AI-driven resource allocation for semiconductor-enabled 6G networks becomes essential when agents are allowed to act and decide on their own, as made possible by AI, edge computing, and integrated sensing and communication technologies.

An adversarial environment can compromise all platforms, fabrics, and remote resources available for agent resource allocation. Although different attack vectors exist, the most damaging ones are the denial-of-service and the data falsification attacks. It is imperative to derive and build defenses against these adversarial conditions by considering trust issues in the development process and ensuring that the reconciling process is able to verify the quality and reliability of the data before accepting it. It is essential to ensure trust and security throughout all the allocation processes.

6.1. Robustness to Adversarial Conditions

A necessary feature of AI-based resource allocation for network control and operation is resilience to internal and external perturbations provoked either deliberately or inadvertently. Internal perturbation can stem from the malfunctioning of network components, Agent's insects or malefic modifications of allocation decisions. Furthermore, situations in which individual agents, as well as groups of agents or the network itself, intentionally deviate from the expected behavior must also be handled properly. The focus here is on such adversarial conditions.

A possible adversarial setting is in which an individual agent can be mistaken as a rogue agent since its actions have a detrimental effect on the overall network performance. To cope with that specific scenario, a defender–attacker game can be formulated by modeling the agents as players of a noncooperative game that can choose to defend or attack the

network, in the latter case optimizing their action for making the performance as bad as possible. The reward for the defender is defined in terms of the connection delay of a particular quality-of-service class, while the reward for the attacker is the inverse of that, indicating a wish to minimize the connection delay of that class. The robustness of such allocation strategies against that action profile is established through a proper Taylor expansion at equilibrium and the solution provides information for assessing the required resilience level, as measured by the cost of the defender strategy.

Equation 5: Multi-agent coordination as a two-sided market + bargaining

The paper states: **two-sided market**, owners form coalitions, consumers bargain

Agentic AI-Driven Intelligent W...

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5.1 Two-sided market primitives

Let:

- resource owners $i \in \mathcal{O}$ supply bundles $b \in \mathcal{B}$
- users $j \in \mathcal{U}$ demand bundles

Owner cost: $c_i(b)$

User value: $v_j(b)$

Social surplus for matching user j to bundle b :

$$\Delta_{j,b} = v_j(b) - \sum_{i \in \text{owners}(b)} c_i(b)$$

A matching chooses assignments $x_{j,b} \in \{0,1\}$:

$$\max_x \sum_{j,b} x_{j,b} \Delta_{j,b} \text{ s.t. feasibility constraints}$$

5.2 Coalition formation



A coalition $C \subseteq \mathcal{O}$ forms to supply a larger bundle; define coalition value $V(C)$ (net surplus it can enable).

A core idea:

- Coalition is stable if no subset can deviate and improve their payoffs.

5.3 Nash bargaining split (step-by-step)

Suppose coalition C and a user j negotiate a deal producing total surplus $S \geq 0$.

Let disagreement utilities be d_C and d_j . Bargained utilities u_C, u_j must satisfy:

$$u_C + u_j = d_C + d_j + S \text{ and } u_C \geq d_C, u_j \geq d_j$$

Nash bargaining solution maximizes:

$$\max_{u_C, u_j} (u_C - d_C)(u_j - d_j)$$

Substitute $u_j = d_j + S - (u_C - d_C)$. Let $x = u_C - d_C$. Then:

$$\max_{0 \leq x \leq S} x(S - x)$$

Derivative:

$$\frac{d}{dx} [x(S - x)] = S - 2x$$

Set to zero:

$$S - 2x = 0 \Rightarrow x^* = \frac{S}{2}$$

So:

$$u_C^* = d_C + \frac{S}{2}, u_j^* = d_j + \frac{S}{2}$$

That's the clean "fair split" baseline; weighted versions exist if parties have different bargaining power.

6.2. Privacy-Preserving Data Sharing

The level of data sharing needed to enable complex control decisions in agentic systems poses significant privacy risks. Therefore, methods must be introduced to facilitate adequate transparency and control while preserving privacy. Solutions generally combine three principles. First, the amount of information collected about users must be minimized. Sharing only data truly necessary for control decisions avoids unnecessary privacy loss. Second, to protect the anonymity of users, data must be anonymised before sharing. For example, in scheduled wireless transmission, rather than revealing the location of users, the general location of groups of users would be shared. When sharing data that may reveal sensitive information about the user, an additional level of anonymisation could be applied, such as shuffling the data among users. Third, the data must be aggregated and stored at a trusted server with only a fraction of the information shared. In this way, information remains private even if shared data is not anonymised.

Privacy-preserving record linkage also offers possibilities for preserving user privacy. In this case, a trusted server links previously anonymised datasets by detecting similar values while ensuring a private domain for each user among all datasets. By introducing trusted servers to oversee data transmission and data-sharing processes, the overall trust in the data-sharing system improves.

6.3. Trust and Verification of Autonomous Decisions

Achieving autonomous allocation of wireless resources relies on agentic AI and must engender trust within the networked society. Trust can be fostered by ensuring that agents explain their resource-allocation decisions. Similarly to human verification of autonomous-system decisions, agents empowered by decision makers capable of conscious internal and external dialogues and complex reasoning (e.g., lateral thinking) are able to articulate these decisions. In particular, they can justify the basis of these decisions, respond to queries about alternatives that could have been



pursued and the reasons why they were dismissed, and express the intuitive and emotional perspectives that motivated the chosen action. The higher the level of such explanation and justification is, the greater its degree of complexity. Because decision-making processes normally differ between agents, enabling auditability is essential.

Independently of agent-level decision explanations, an external assessment of the validity of an agent decision tends to engender trust, especially in critical situations. Users must thus be capable of verifying whether an autonomous resource-adjustment decision is genuine, identifying which agent has applied it, establishing the legitimacy of the entity that has provided the agent with control over the resource and the action itself, and ensuring that the decision-maker agent has authority over the considered resource. A provenance-tracking mechanism can ensure that all these requirements are met.

7. Conclusion

Research introduced a system architecture for agentic AI-driven wireless resource allocation systems in semiconductor-enabled 6G networks. Control functions were grouped into cognitive loops, with perception involving contextual information sensing, decision-making combining policy learning and model predictive planning, and action comprising allocation adjustment and network adaptation. Concrete algorithms were defined for three representative cognitive functions: dynamic scheduling via single-agent reinforcement learning, multi-agent resource coordination through bargaining negotiation, and causal inference for detectability and explainability of allocation decisions.

Open issues encompass sample-efficient training of cognitive functions, establishment of high-priority resource arbitrators, rapid deployment of coalition-based resource coordination, detailed derivation of trust metrics within disturbances, and management of supply and trust data in privacy-sensitive settings. Anticipated trends include enhancement of the cognitive loop concept through multi-

model contextual modeling, integration of causal inference and mission-oriented axiomatic design into agentic allocation, consolidation of agent-oriented control in tactical edge-AI architectures, and interplay of agent-based control and novel economic approaches in market-oriented networks. These advances will influence standardization, deployment, and use of agentic AI-driven resource allocation.

Equation 6: Causal inference + counterfactual explainability (do-calculus)

6.1 Structural causal model (SCM)

Let:

- X = context features (load, SINR distribution, mobility class, etc.)
- A = allocation decision (action)
- Y = outcome (dropped packets)

SCM:

$$X := f_X(U_X), A := f_A(X, U_A), Y := f_Y(X, A, U_Y)$$

DAG: $X \rightarrow A, X \rightarrow Y, A \rightarrow Y$

6.2 Observational vs interventional

Observational conditional:

$$P(Y | A = a, X = x)$$

Interventional:

$$P(Y | do(A = a), X = x)$$

If there is no unobserved confounder between A and Y once we condition on X , then:

$$P(Y | do(A = a), X = x) = P(Y | A = a, X = x)$$

6.3 Average treatment effect for allocations



Compare two allocations a and a' :

$$\text{ATE}(a, a') = \mathbb{E}[Y \mid \text{do}(A = a)] - \mathbb{E}[Y \mid \text{do}(A = a')]$$

6.4 Counterfactual explanation

Given an observed episode with (x, a, y) , ask:

“What would the dropped packets have been if we had chosen a' instead?”

Counterfactual:

$$Y_{a'}(u) = f_Y(x, a', u_Y)$$

An explainable agent can report:

$$\Delta = \mathbb{E}[Y \mid \text{do}(A = a'), X = x] - \mathbb{E}[Y \mid \text{do}(A = a), X = x]$$

and interpret Δ as “expected drop change if we switch the action”.

7.1. Future Trends

Open problems in agentic AI-driven resource allocation center on the three angles of agent autonomy: actions, policy creation, and data sharing. At the lowest decision-making tier, the selection of control actions that maintain QoS while satisfying performance constraints without incurring unnecessary overhead is critical, especially when considering the large number of target resources and the multitude of competing users. Balancing exploration and exploitation remains an open question, as does achieving efficient sample complexity for setting an elusive RL agent reward. Considerations of causality can help improve the interpretability and transparency of action selection.

Coordination between multiple resource-allocation agents raises questions of how to share resources when a direct conflict arises and how to form a coalition when a collaboration presents mutual advantage. Autonomous decisions also necessitate the verification of all input data used in the decision-making process, which is particularly relevant in adversarial environments. Sampling only data

that is easily verifiable by the agent could form a basis for strategies to satisfy externally imposed trust requirements with low cost. Such strategies should be discussed within the context of the type of data being used, the context of allocation, and the agent's position.

Beyond these open problems, an exciting aspect of agentic AI-driven resource allocation lies in its close alignment with anticipated key trends for the next generation of telecommunications. Efforts to minimize the need for human intervention also extend to autonomous networking, in which policies are created by agents for their own use. Such policies can generate less overhead than controller decisions, enabling new avenues of research in the area of resource-sharing negotiations between agents. Efforts to share as little information as possible while ensuring high-quality decisions naturally combine with the need to optimize data transmission in adversarial environments. Collectively, these lines of inquiry will ultimately lead to the creation of trustworthy and ethical allocations.

8. References

1. Abdel Wahab, O. A., Mourad, A., Otrok, H., & Taleb, T. (2021). Federated machine learning: Survey, multi-level classification, desirable criteria and future directions in communication and networking systems. *IEEE Communications Surveys & Tutorials*, 23(2), 1342–1397.
2. Baccour, E., Allahham, M. S., Erbad, A., Mohamed, A., Hussein, A. R., & Hamdi, M. (2023). Zero touch realization of pervasive artificial intelligence as a service in 6G networks. *IEEE Communications Magazine*, 61(2), 110–116.
3. Bouzinis, P. S., Diamantoulakis, P. D., & Karagiannis, G. K. (2022). Incentive-based delay minimization for 6G-enabled wireless federated learning. *Frontiers in Communications and Networks*, 3, Article 827105.



4. Aravind, R., Surabhi, S. N. D., & Shah, C. V. (2023). Remote Vehicle Access: Leveraging Cloud Infrastructure for Secure and Efficient OTA Updates with Advanced AI. *Eur. Econ. Lett.*, 13, 1309-1319.
5. Calvanese Strinati, E., & Barbarossa, S. (2021). 6G networks: Beyond Shannon towards semantic and goal-oriented communications. *Computer Networks*, 190, Article 107930.
6. Gupta, R., Reebadiya, D., & Tanwar, S. (2021). 6G-enabled edge intelligence for ultra-reliable low latency applications: Vision and mission. *Computer Standards & Interfaces*, 77, Article 103521.
7. Hossain, A. R., Liu, W., Ansari, N., Kiani, A., & Saboorian, T. (2023). AI-native for 6G core network configuration. *IEEE Networking Letters*, 5(4), 255–259.
8. Hoydis, J., Ait Aoudia, F., Valcarce, A., & Viswanathan, H. (2021). Toward a 6G AI-native air interface. *IEEE Communications Magazine*, 59(5), 76–81.
9. Huo, Y., Lin, X., Di, B., Zhang, H., Hernando, F. J. L., Tan, A. S., Mumtaz, S., Demir, Ö. T., & Chen-Hu, K. (2023). Technology trends for massive MIMO towards 6G. *Sensors*, 23(13), 6062.
10. Iyer, S. (2023). Machine learning enabled dynamic spectrum access for 6G wireless networks. *Journal of Applied Security Research*, 19(2), 330–350.
11. Khan, L. U., Saad, W., Niyato, D., Han, Z., & Hong, C. S. (2022). Digital-twin-enabled 6G: Vision, architectural trends, and future directions. *IEEE Communications Magazine*, 60(1), 74–80.
12. Ohtsuki, T. (2023). Machine learning in 6G wireless communications. *IEICE Transactions on Communications*, E106-B(2), 75–83.
13. Yandamuri, U. S. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. *International Journal Of Finance*, 36(6), 682-706.
14. Pan, C., Ren, H., Wang, K., Kolb, J. F., El Kashlan, M., Chen, M., Di Renzo, M., Hao, Y., Wang, J., Swindlehurst, A. L., You, X., & Hanzo, L. (2021). Reconfigurable intelligent surfaces for 6G systems: Principles, applications, and research directions. *IEEE Communications Magazine*, 59(6), 14–20.
15. Patil, A., Iyer, S., & Pandya, R. J. (2022). A survey of machine learning algorithms for 6G wireless networks. *Journal of Information Processing Systems*, 18(6), 761–775.
16. Pokhrel, S. R. (2022). Learning from data streams for automation and orchestration of 6G industrial IoT: Toward a semantic communication framework. *Neural Computing and Applications*, 34, 15197–15206.
17. Sen, P., Ariyaratna, V., Madanayake, A., & Jornet, J. M. (2021). A versatile experimental testbed for ultrabroadband communication networks above 100 GHz. *Computer Networks*, 193, Article 108092.
18. Shafie, A., Yang, N., Han, C., Jornet, J. M., Juntti, M., & Kürner, T. (2023). Terahertz communications for 6G and beyond wireless networks: Challenges, key advancements, and opportunities. *IEEE Network*, 37(3), 162–169.
19. Shi, Y., Lian, L., Shi, Y., Wang, Z., Zhou, Y., Fu, L., Bai, L., Zhang, J., & Zhang, W. (2023). Machine learning for large-scale optimization in 6G wireless networks. *IEEE Communications Surveys & Tutorials*, 25(4), 2088–2132.
20. Shome, D., & Waqar, O. (2022). Federated learning and next generation wireless communications: A survey on bidirectional relationship. *Transactions on Emerging Telecommunications Technologies*, 33(7), Article e4458.
21. Song, W. (2021). Reconfigurable intelligent surface-based space-time block transmission on 6G. *Wireless Communications and Mobile Computing*, 2021, Article 5569006.
22. Sun, Y., et al. (2022). Artificial intelligence and machine learning for 6G networks. *IEEE Communications Surveys & Tutorials*, 24(2), 1221–1261.
23. Venkatesh, S., Lu, X., Tang, B., & Sengupta, K. (2021). Secure space-time-modulated millimetre-wave wireless links that are resilient to distributed eavesdropper attacks. *Nature Electronics*, 4, 827–836.
24. Wu, W., Zhou, C., Li, M., Wu, H., Zhou, H., Zhang, N., Shen, X. S., & Zhuang, W. (2022). AI-native network



- slicing for 6G networks. *IEEE Wireless Communications*, 29(1), 96–103.
25. Yang, W., Du, H., Liew, Z. Q., Lim, W. Y. B., Xiong, Z., Niyato, D., Chi, X., Shen, X., & Miao, C. (2023). Semantic communications for future Internet: Fundamentals, applications, and challenges. *IEEE Communications Surveys & Tutorials*, 25(1), 213–250.
 26. Yang, Z., Chen, M., Wong, K.-K., Poor, H. V., & Cui, S. (2022). Federated learning for 6G: Applications, challenges, and opportunities. *Engineering*, 8, 33–41.
 27. Mangalampalli, B. M. Generative AI Applications In Healthcare Data Mart Design And Optimization.
 28. You, X., Wang, C. X., Huang, J., Gao, X., Zhang, Z., Wang, M., Huang, Y., Zhang, C., Jiang, Y., Wang, J., Zhu, M., Sheng, B., Wang, D., Pan, Z., Zhu, P., Yang, Y., Liu, Z., Zhang, P., Tao, X., ... Liang, Y.-C. (2021). Towards 6G wireless communication networks: Vision, enabling technologies, and new paradigm shifts. *Science China Information Sciences*, 64(1), Article 110301.