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Agentic AI for Autonomous Network Orchestration: A New Frontier in Telecommunications

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Abstract: The telecommunications industry is undergoing a transformative shift driven by the increasing complexity, scale, and dynamism of modern networks, particularly with the advent of 5G, edge computing, and cloud-native infrastructures. Traditional network management approaches—often rule-based, centralized, and reactive—are becoming inadequate to meet the demands of ultra-low latency, massive device connectivity, and highly dynamic service environments. In this context, agentic artificial intelligence (AI) emerges as a promising paradigm for achieving autonomous network orchestration. Agentic AI systems are characterized by their ability to operate as goal-driven, context-aware, and self-directed entities capable of making real-time decisions, learning from interactions, and collaborating or negotiating with other agents to fulfill complex objectives.

This paper explores the integration of agentic AI into telecommunications networks to enable autonomous orchestration across heterogeneous domains. By leveraging multi-agent systems, reinforcement learning, digital twins, and intent-based networking, agentic AI can facilitate adaptive and proactive management of network resources, service assurance, and fault resolution without human intervention. We examine key architectural components required for enabling agentic orchestration, such as distributed intelligence, secure communication protocols, and real-time data analytics. Additionally, we analyze practical use cases including automated service provisioning, dynamic spectrum allocation, and self-healing network behaviors.

The deployment of agentic AI in telecommunications presents not only technical opportunities but also challenges related to interoperability, transparency, trust, and governance. This paper proposes a framework for safe and scalable adoption, emphasizing the importance of standardization, ethical design, and cross-domain collaboration. By pushing the boundaries of autonomy and intelligence in network management, agentic AI offers a new frontier for telecom operators seeking to reduce operational complexity, increase efficiency, and deliver next-generation connectivity experiences. We conclude with a vision for the future of intelligent, self-orchestrating networks powered by agentic AI, laying the groundwork for further research and innovation.

Keywords: Agentic AI , Autonomous Systems , Network Orchestration , Telecommunications –,Self-Optimizing Networks (SON) , Intent-Based Networking , Multi-Agent Systems –,AI-Driven Automation , 5G/6G Networks –,Real-Time Decision-Making , Network Intelligence , Edge Computing , Dynamic Resource Allocation –,Cognitive Networks –,Zero-Touch Management

1. Introduction

Today's widely distributed network involving millions of end devices raises challenges in terms of efficient and effective sharing of system resources. Unlike conventional on-premise networks, networking and computing footprints have evolved to include non-conventional Devices & Edge Nodes (e.g. IoT devices, edge gateways, on-board intelligence), and hence more diverse, distributed nodes in cloud locations (e.g. fog, cloudlet, private cloud, public cloud). Resources are also virtualised and standardised to compose service delivery chains on demand, e.g., Virtual Network Function (VNF) chaining on demand to deliver telecom services in core networks [1]. More importantly, resource demand and supply are more dynamic depending on user mobility and user/service context changes. It has been widely accepted that artificial intelligence (AI) techniques need to be investigated and exploited within recommendation and decision policies of domain-specific orchestration. With specific regards to the orchestration of a virtualised and distributed network slicing (NS) framework, key orchestration challenges require AI/agentic intelligence to deal with service quality/SLA-aware resource demand and capability discovery, compositional synthesis, elastic lifecycle assistance, and failure recovery. It is broadly acknowledged that 5G and beyond networks need distributed and hierarchical orchestration. Specifically, a central domain orchestrator may flexibly decompose a complex networking and computing service to multiple network and/or cloud domain orchestrators to improve deployment latency, durability, and overall robust quality. Several open-source projects and platform solutions exist, focusing on one single domain, but none covering a distributed multiple domain solution [2]. Orchestration policies and SLAs need to account for the distributed nature of networks, cloud, and services. Concrete open-source orchestration and management APIs of multiple domains are needed; built on a unified mindset, modelling, and language. Orchestration KLs and ontologies are to be standardised. A switching mechanism is also needed to commission robots' modelling, planning technique, decision policy, feedback and learn methods.

3. The Role of AI in Telecommunications

The first wave of AI projects relied on traditional machine learning with forecast techniques like exponential smoothing and ARIMA. However, the second wave with applications such as neural networks, ensemble methods, and multi-agent systems has proven to be more suitable for telecommunications networks. With the massive increase in generated data, handling the use of complex AI algorithms will become a fundamental requirement. It is anticipated that the third wave of AI will address both high data complexity and knowledge, and it will characterize networks more intricately with respect to physical characteristics, services, and networks

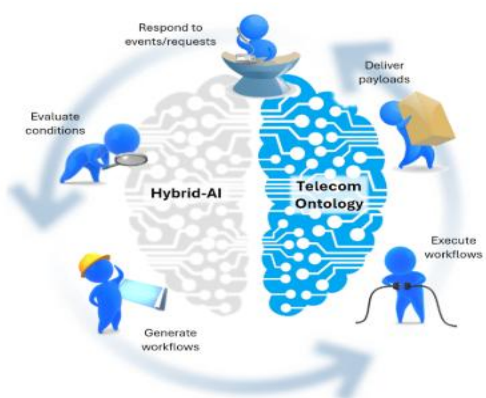

Fig 1: Agentic Automation.

The third wave of AI approaches relies heavily on a more detailed mapping of the knowledge domain of telecommunication networks. As a consequence, it is expected that telecommunication networks will be characterized with respect to their structure, function, and usage through multi-layer based network topology detection, service discovery, and Multi-agent System (MAS)-based knowledge representation, inference, and reasoning techniques for better planning, organization, and optimization of network performance. It will be anticipated that the rise of this third wave of AI will also eventually change the architecture of telecom networks, for example by deploying capable edge routers that would be capable of seamlessly connecting operator rooted transport networks with rich application / service provider networks and the public Internet.

It is generally understood in the AI domain that agentification refers to the process of transferring knowledge representation and algorithmic implementation from a centralized solution to a strongly decentralized one. It is expected that a significant part of the knowledge and algorithms and the respective abstractions will need to be modified and re-implemented in order to break down complex problems within so-called agent societies. Fortunately, knowledge and algorithms to perform the translation and abstraction from centralized to multi-agent systems (and vice versa) are available and can be adapted to the telecommunication environment. It is anticipated that the knowledge and algorithmic level of telecom networks and the respective AI implementation will migrate from a more centralized to an increasingly decentralized solution with agentification representing multi-stage implementation path.

4. Key Technologies in Agentic AI

With the advance of artificial intelligence (AI), the emergence of new AI systems marks the direction towards artificial general intelligence (AGI). To implement AGI, the concept of interactive AI (IAI) has been introduced, which can interactively understand and respond to human user input and dynamic system and network conditions. This section explores an integration and enhancement of IAI in networking. Recent developments and future perspectives of AI are discussed, and the technology and components of IAI are introduced. The integration of IAI into next-generation networks is then explored, focusing on how interactions can enhance network functionality, improve user experience, and promote efficient network management. Finally, potential research directions for IAI-based networks are discussed.

The growing size and complexity of networked systems have been driving the development of automated control mechanisms by human designers. AI has been viewed as a promising approach to the development of automated control mechanisms. The AI techniques, models, and applications for networking have developed rapidly in recent years. In terms of techniques, experts have been leveraging traditional machine learning (ML) methods such as clustering, regression, and decision trees as well as developing new AI methods, such as deep learning (DL), transfer learning, and probabilistic graphical models. In terms of models, autonomous agents, federated learning models, latent variable models, reinforcement learning (RL), and AI transformers have been proposed and applied. In terms of application areas, AI has brought insight into connection scenarios, fault diagnosis, network design, protocol optimization, equipment configuration, and resource allocation tasks, among others.

The potential advantages of AI for networking can be summarized into higher automation, lower operational costs, and more intelligent mechanisms than conventional rule-based approaches. With AI, complex networked systems can possibly learn hidden patterns via data-driven analysis and analysis-guided reactive control. AI decisions are incrementally learned over time, leading to increasingly robust automation. In addition, AI has the potential to learn human-like interactive and incremental decision strategies to mitigate design limitations.

With rapid advances in AI capabilities, an unprecedented AI revolution has been expected in many fields and industries, including therapy, gaming, finance, design, education, and transportation. AI has become a topic of public interest, and its prospect is under growing concern. As a means to machine autonomy, the possibility of more capable and general AI systems, such as AGI, is drawing more attention. In many people's views, agentic AI, which can autonomously formulate and execute tasks without extensive human input, will change the world and raise social concerns.

Eqn.1: Agent Objective Function (Reinforcement Learning Framework)

$$J(\pi) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right]$$

- π: policy (mapping from state to action)
- s_t: network state at time t
- a_t: action taken at time t
- $R(s_t, a_t)$: reward function (e.g., QoS improvement, resource efficiency)
- γ: discount factor ($0 < \gamma < 1$)

4.1. Machine Learning Algorithms In the context of network automation and orchestration, the need for specifying and monitoring network intents has gained prominence. Intent-based networks are an instance of policy-based networks where intents are high-level constraints fulfilling the business logic. Machine-learning algorithms have emerged as a candidate for achieving intents for various areas in the telecommunication network, such as classification, prediction, and detection. However, deploying ML pipelines poses challenges like a diverse ML algorithm landscape, Model Performance KPIs, and explainability. In this context, the orchestration of the ML pipelines promises better manageability and usability of various ML pipelines in a diverse environment.

MLFO enables intent-based orchestration and management of ML pipelines at two levels: global orchestration and local orchestration. The high-level architecture of the framework consists of an MLFO controller, MLFO agents, and an ML pipeline repository. The MLFO controller communicates with MLFO agents through a protocol. The MLFO agents communicate amongst each other and with the MLFO controller utilizing high-level intent orchestration description. The ML pipeline repository contains ML pipeline templates as artifacts that can be executed. The orchestration framework supports autonomy of MLFO agents in managing the ML pipeline lifecycle, while the MLFO controller is responsible for intent orchestration.

The ML pipeline orchestration relies on various machine-learning algorithms that can achieve a network intent. Several varieties of ML algorithms exist, such as supervised learning, unsupervised learning, reinforcement learning, deep learning, and cyber-physical ML. To effectively orchestrate ML pipelines, ML algorithm orchestration entails discovering new or replica ML pipelines that can achieve a given intent. Various orchestration strategies broadly can be categorised into ML pipeline composition and ML pipeline suppression. Pipeline Composition consists of discovering new ML pipelines to accomplish a given task. Pipeline Suppression entails finding ML pipelines among existing pipelines that do not satisfy the KPIs.

4.2. Natural Language Processing A large number of tools, DSLs, and codebases have been produced for network management use cases like capacity planning. This is driven by the fast adoption of cloud computing, which has made SDNs more complex and harder to manage. Existing network configuration/routing DSLs are very diverse and comparison at a higher level does not exist. In general, they can be categorized as “general purpose” and “domain specific”. Employing LLMs can help with this challenge, as they could provide a high-level understanding of these DSLs and offer an abstraction to work with that is much simpler than directly using them. This bridge between tools and DSLs is one of the main motivations behind FlexNN.

Language models (LMs) have the ability to interpret human language in a way comparable to human understanding. They produce outputs that, despite being examples of LLM hallucination, are syntactically and semantically equivalent to human-written code. An effective experimental setup to understand what LLMs learn about DSLs and whether it can translate explanations given in natural language to these DSLs is suggested. This is the main experiment of FlexNN framework. Ensembles of LLMs improve system accuracy across all metrics and reasonable assumptions about complexity lead to dramatic runtime savings.

FlexNN enables users to ask questions in natural language for use cases such as “is there congestion? If so, can you fix it?” At its core is the understanding that a “use case” can be understood as a graph manipulation task. The user question is interpreted by the LLM and the corresponding queries are automatically delivered to the underlying graph tool. The results are then produced and can be either visualized or re-expressed in natural language [4].

LSMs solve potential issues regarding robustness and interpretability of LLMs. Robustness refers to the models being able to still provide an acceptable answer when requiring substantiated, multi-hop reasoning on very large graphs instead of over-injecting noise into the input. To achieve this, a higher-level approach for DSLs was proposed that mimics how humans compute on graphs. A combination of graph embeddings and reasoning templates was implemented. It was shown that this model is highly accurate compared to the finetuned LLMs and improves robustness a lot. Spectral embeddings in the semi-supervised setting and on a different query class scale very well compared to bottleneck architectures. This only partially addresses the robustness issue, but provides insights.

4.3. Data Analytics Techniques At the centre of network data analytics frameworks is the analytics literacy architecture, which deals with analytics culture, skills and governance. The culture deals with KPIs and their related actions while skills concern the availability of self-services and the presence of scientists. Connectivity concerns the availability of the resources needed for analytics activities while data management and openness incorporate data standardisation and data governance aspects. As regards algorithms and tools, there are infrastructure and indications datasets as well as analytics exploration and production tooling. Analytics routines capture the activities necessary for the execution of analytics projects with a view of transforming raw data into knowledge essential for analytics consumability. It includes capture of data, cleansing, quality assessment, and transformation for enabling exploration. Systems, KPIs and actions dimensions deal with the consumption of the factual knowledge. Analytics translation concerns the understanding associated with the knowledge. Furthermore, the architectural representation of the network data pre-processing and exploration process for a holistic network data analytics framework is also sketched. Finally, the inclusion of expert inputs in terms of end-users who take part in knowledge consumability scalability evaluations before the triggered actions is detailed. Guidelines for future work are given [5]. The AI/ML technology aims to achieve an intelligent orchestration that requires no (or minimal) human intervention at any level. Regarding orchestration mechanisms, the AI/ML service management may be either centralised, which means that all managed resources are orchestrated in one central point of control, or federate or hierarchical, by which orchestration may need to be distributed in multiple orchestration components. To fulfil the federate or hierarchical orchestration strategies, an orchestrator-to-orchestrator paradigm can be leveraged, by which different orchestration entities, either in the same or different technology layers, may interact, sharing resource information and collaborating in the decision-making and action-taking processes. Regardless of the performance targets, algorithms and AI mechanisms, the layered architecture has to stipulate interfaces across the layers both for data and control-plane information regarding managed entities .

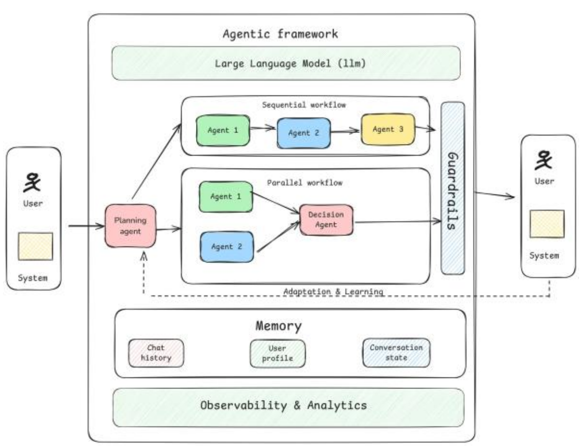

Fig 2: Understanding Agentic AI Architecture

5. Benefits of Autonomous Network Orchestration

The growing need for 5G services, together with the evolution of infrastructures and systems based on software-defined networks (SDN) or network function virtualisation (NFV), has spurred the search for new ways of orchestrating hardware resources. Providers of information technology/communication technology (IT/CT) services should seek solutions to completely abstract, virtualise and automate their control of such resources. This is challenging as it requires negotiating and managing infrastructure services across multiple providers, some of which may be heavily over-provisioned or only partially controllable. Nevertheless, by developing the concept of abstraction of resource pools through a modelling language based on YANG data models and REST-based API, it is possible to encapsulate complexity and create new software products that enable unintrusive, simple and predictable virtualisation of bandwidth and processing power and "zero-touch" orchestration and day-2 management of infrastructures originally designed and deployed as silo solutions [7].

Network slicing should be conceived of by combining network services with resource-related demands, either on-tenants-enabling controlled dynamic topologies and efficiently matching service-to-resource graphs. This control level composition should account for and control a series of complex functions including topologies and graph composition, resource pool discovery and provisioning, embedded graph decomposition, parameterisation, compatibility check, and execution following synchronous distributed analytics for gradually re-optimising minimum-service-resource pair graphs at execution-time. Network monitoring, as the other end of the control loop, relies on feedback from network fixtures-all kinds of generic sensors translating the state of the networks into a common data model so control functions can exploit it .

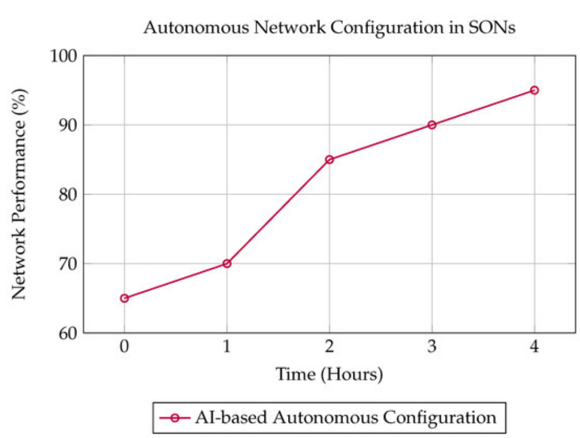

Fig : Enhancing Communication Networks

5.1. Increased Efficiency As demand grows for heterogeneous network services, including 5G, growth of QoS "on demand" network services, IoT, etc., capabilities need discovery, chaining, placement. The new autonomous network consists of a number of autonomous controllers looking after many mutually dependent network components across nodes and as well orchestrate the required resources from different domains. Each controller has an innate view of its own domain, but agentic behavior ensures network-wide selection and balance of QoS-efficient orchestrations through disposition of global domain state. For each discovery, QoS discovery of service candidates across domains with negotiation of resource requirements comes up. Also, through specialized agents, higher QoS service chains can also be built up incrementally. New computation resources may also be provisioned uniformly across vendors for domain-wide switching of excess load. Needed capabilities may include QoS-efficient discovery, provision handling/bidding, load simulation, and packet routing. Active participation of these needed roles, while covering all such capable domains of knowledge, lead to autonomous orchestration. Furthermore, with a specialized active agent, end to end QoS provisioning through multi-domain chaining is enabled. As the overlays provide QoS-efficient chaining of candidate services across domains, protocols ensure service instantiation and chain packet switching.

Since Video-on-Demand (VoD) is being prominent, as service plans to widen to live streaming and VR, to meet quality demand for new live services, access and core networks are planning to be upgraded to 1 Gbps using optical circuit-switching networks. Besides for different channel provisioning, multicast capability and its automation in networks is expected for service offerings to many viewers simultaneously. A controller keeps track of the topology on one side and a knowledge-based controller suggesting efficient circuit links for QoS specification on the other side would interact with CPEs for service instantiating or rerouting if needed, which are taking care of the on-goings of the domain.

5.2. Cost Reduction The proposal of Agentic AI for autonomous network orchestration leads directly to multiple avenues for cost reduction. The resulting new cloud-native wano architecture will remove cloud provider costs associated with cloud-to-edge transfer of network orchestration control traffic and increase the understanding of networks and applications. This increase in understanding will be due to network telemetry data being additional knowledge about agentic states. It will also be due to new cloud-native WANO orchestration software being able to export a single agent-based observation to globally explain new policy actions taken by the ensemble of agent-based agents that all improve the total overall reward function. Both of these savings will occur in addition to stateless agentic algorithms being able to detect problems more accurately and faster than Stateful AI used today and also find mitigation strategies better than planned solutions.

The automated labelling systems for cloud-native AINOs promise a new set of optional services that will cost less than equivalent services for today’s cloud-based networks. Applications in LANs for more cost-effective decision-making at the edge will also use cloud-native AINOs. Traditional equipment developers will need to refocus operations on creating new 5G+ equipment. Operating costs will be lowered by new decreasing cost passed by cloud users to cloud providers who will have greater levels of agentic automation [9] [10]. The much earlier and more rapid network convergence of consumer LANs and backhaul and enterprise wireless systems will be facilitated by the dense deployment of small cells using edge computing and the increasing granularity of resource allocation. In addition, with true cloud-native hardware, software and orchestration techniques, music distribution and gaming applications will be able to obtain on-demand once in a lifetime, zero-latency resource allocation at a potentially infinitely large text-to-music and game orchestrated source which is cost-competitive with lower quality provision.

5.3. Enhanced Network Reliability Increased reliability is expected from the use of AI-based agents in autonomous orchestration. This reliability can be ensured in several ways, including proper isolation between agents, ensemble-based learning or decisions, and considered handover over time. Moreover, there are two ways in which actions taken by a single agent can be rendered more reliable. First of all, agents can be made conform to a specific behaviour model. This model may have been derived from Machine Learning since a high number of collective e.g. control or learning experiences. However, functionality provided by a model may underutilise the potential capability of the model; thus, a Solid-State Drive (SSD) network element may be operated as a Ferrite-based Magnetic Hard Disk (HDD). Second, agents can keep with an explicit likelihood or credits distribution on their knowledge, e.g. heuristic information about routes in a network, ongoing policies, etc. Provided with this additional information, agents can dynamically adjust the way they query, combine, or exploit knowledge when recommendations from other agents are received.

Strong reliability expectations may arise at any stage of the orchestration process. Here, however, two stages stand out: an unsolved issue on what should be doing by a single agent is to be considered here, the distributive nature of the process implies a minimum level of collective intelligence that a CiC must present, discussion here thus focuses on that stage of orchestration that is collective, more reliable information and/or actions on that stage is a priority. When inquiring autonomously, at least trouble be avoided, or be kept as small as possible [8]. Currently, out-of-the-box agents are responsible for more total information requests and also for more of the specific network data at stake. Some immediate priorities are firstly to ensure that information collected by agents is explicitly available to more agents to be exploited be them also. Request-free knowledge dissemination either may level out workloads; it is, however, also of paramount importance for owned information getting piled in a single agent.

Fig 3: Agentic AI in Telecom Industry

6. Challenges in Implementing Agentic AI

The rapid development in artificial intelligence (AI) has made its implementation feasible in fields such as computing, networking, robotics/perception/automation, but remains unripe in the end-to-end telecommunication. It is believed that agentic AI, inherently capable and perceptive AI with intelligence (e.g. knowledge, reasoning, planning), could significantly ease operation and management in cloud-native, complex, and dynamic networks with heterogeneous, distributed, and intelligent components. However, whether and how to harness agentic AI for network orchestration is an open question. Both agentic AI and relevant systems/service requirements have reached a level of maturity but are yet aggregated well for implementation in this critical industry. This paper reconsiders AI actors, competence models, and necessary co-actors for ordinality, safety, and intelligibility, from tasking and learning to system capacity and reachability, to systematically inform generations of agentic AI towards orchestrating autonomous networks. Other pitfalls across capacities, interpretability, and relevance, concerning AI actors and service requirements, are expected to face serious challenges, including knowledge traps, reasoning inconvenient nightmare, capto queries diversity doubts, aspiration stochastic efficiency, and netevolution dimensions crises.

The fundamental nature of modern telecoms creates an uncontested imperative for a level of AI for networks that has never previously existed, as AI delivery and responsiveness are increasingly intertwined with all aspects of the telecom service duality. Just as legacy networks reached full performance equivalence and interface crispness as a function of time/space convergence, employment models in future end-to-end networks will evolve to incorporate a corresponding high level of AI participation alongside ever-stricter expectations [11]. Determination of a single AI framework would be naive, unreduced within the unprecedented complexity and necessary attenuation of bandwidth for interoperability. Determination of a global equilibrium between performance expectations and AI netreachability or AI capabilities for networks would be equally naive, renewed population pressures leading to netblockage of unintended consequences.

6.1. Data Privacy Concerns The fifth-generation of core networks has become increasingly digitalized. Greater resource efficiency, return through automation, cost reduction, and network observability and integrity have been sought by transitioning from legacy, hardware, connection-oriented designs to model-driven, portable and software-defined solutions. Enterprises and their ecosystems aspire to achieve near-zero touch management of networks across domains in a highly dynamic and interconnected landscape through pervasive and ubiquitous Artificial Intelligence (AI). The tremendous complexity and scale of automated networks call for AI that is predominantly agentic, adaptive, bounds itself by acceptability, with an ability to confer a distinct strategy to advanced autonomous decision making, with some degree of foresightedness. However, there are several concerns surrounding threats towards safety and security, privacy, resilience, trustworthiness, and explainability that need to be considered with care when enhancing the capabilities of AI in future intelligent networks. Privacy is a significant concern that typically arises when employing learning from data in a collaborative fashion, where users are often resistant to share anything proprietary. This forms a barrier for agents to learn efficiently from an abundance of data co-located at cloud-enabled infrastructures and in the environments. Generally, privacy issues are inherent to all AI methods relying on sensitive data in a federated or collaborative setting. With a strong motivation driven by flourishing business opportunities, various privacy concerns are addressed in different AI paradigms, including Learning with Privacy (LwP)-based methods in Deep Learning (DL) and Multi-Agent Reinforcement Learning (MARL) [12].

By employing different learning methods, a directive structure from central to edge nodes and a pooling mechanism are typically needed to federate knowledge and keep data confidential and de-identified. The cloud-stratum collaborator models a promoter that coordinates and delegates tasks among data owners, hosts/re-trains learning frameworks, and refrains from ever direct access of agents' data. The second concerns regarding privacy are raised from the channels induced by the knowledge transfer: possessing the knowledge current and/or past, either local or aggregated, gives agents the potential to reconstruct the state-message pairs seen and thus breach privacy. Knowledge transfer protocols aim to inhibit such reverse engineering a.k.a reconstruction attacks, which may further involve post-processing of the learning output. Privacy classical approaches involve Cryptography, Data Sanitization, Differential Privacy (DP), and Multi-agent learning protocols: Cryptography methods incur much overheads with a linearly growing communication overhead and non-uniform provisioning of network resources.

$$J_{global} = \sum_{i=1}^{N} \mathbb{E}_{\pi_i} \left[\sum_{t=0}^{\infty} \gamma^t R_i(s_t, a_t^i) \right]$$

Eqn.2: Multi-Agent Collaboration

- a_t^i: action taken by agent i
- Agents may communicate or negotiate based on shared policies or incentives.

Objective6.2. Integration with Existing Systems Network orchestration incorporates multiple network technologies and topologies. The unique requirements of each network technology must be translated and integrated into a common logical model for orchestrating services across multiple domains. Each unique technology has a distinct set of models for describing elements such as the physical network topology, data path, nodes, and optical components. Information models define and structure the data exposed by device-specific software and the network element controllers required to access them. Therefore, the orchestration software must map indigenous information models onto a common information model that describes all network-wide initial states. After mapping to a common model, service connection requirements should be translated into a specific technology-related model. Finally, component-specific orchestration software is executed to configure service components in all relevant elements of the engineered network. The corresponding technology-agnostic, common, and specific information models should support the specification of initial states onto the orchestration and network element controllers.

Open standard protocols exist for the configuration and monitoring of network management systems, orchestration modules, resource controllers, and network elements at multiple logical and functional abstraction levels. A simple standard protocol for topology pull and service requests is absent. In addition to supporting the standard specification and pulling of network and service request topology information with full coverage, the protocol should allow checking topology dependencies among network elements of different types while interfacing with technologically heterogeneous devices. The protocol's design should also serve as an enabler to implement further extensions to cover the complementary needs of configuration, monitoring, and event notification. The interactions among the model, protocol, and complementary software components should result in the self-contained orchestration of a heterogeneous multi-technology transport network [6].

6.3. Scalability Issues

The previous chapters have identified a number of issues that must be addressed in order to establish LLMs as foundational AI technology for management and orchestration of slicing networks in 5G networks. However, a closing chapter addressing issues of scalability is now warranted. As outlined in previous chapters, AI-based tools can assist Network Slicing Management (NSM) by encoding background knowledge in prompt engineering and by offering few-shot inferences on slices with LLMs. While—and indeed, perhaps especially—as LLMs range further and further into more complex domains, it cannot simply be assumed that the fundamental architectures underlying these models will easily scale to new and novel domains with complex interfaces and diverse modes of interaction. Rather than represent a simple extension of current non-scatter architecture—a promising route to further exploration in its own right—a robust LLM solution for NSM must account for some of the obstacles that this domain represents.

Through the embedding of structured knowledge bases generated from model development in previous chapters, promising steps towards the minimization of the gap between a narrow range of pre-programmed tasks and an open-ended domain of candidate queries have been presented. To recap and exemplify these points, the previously displayed model allows the modelling of a variety of complex requests and the sequential mapping of predictions through either graph- or pipeline models to quantifiable metrics at their termination point. These techniques for knowledge base matching and search represent only a few out of a plethora of potential avenues for exploration and further research. However, even so, they only scratch the surface of the architecturally disparate subdomains that belong to the general class of Network Slicing Management (NSM).

The vast array of graph formalizations for monitoring, resource allocation, and overall task representation traverses a diverse space with many isolated examples. These include load balancing using multi agent reinforcement learning, multi-objective NSM combining planning with deep learning, and an LLM-based interface for discrete graph queries. Solving problems represented in other media using LLMs, such as mathematical expressions and programming languages, will also constitute paradigms for future research in the domain of NSM and its applications. A closing emphasis on the dizzying scope of disciplines and techniques included within NSM portraits an intellectual skyline far beyond the capabilities of any individual researcher or existing research team.

7. Case Studies of Agentic AI in Action

AI systems are being deployed for new, increasingly impactful applications that have effects on many people's lives. As these systems are created, deployed, and utilized, AI researchers ought to think of their own personal responsibility with regard to their work. Largely, the outcomes of previous advanced technologies have been positive; intelligent software for improving cancer diagnosis, computer safety features in cars, and many other useful and productive applications [13]. But as previously unavailable amounts of computing power are purchased, and improved techniques are found, intelligent software is being adopted in new and new contexts. Many of these contexts affect the lives of many people, and as the use of AI enters new domains, negative effects of its failures and design flaws are also becoming more visible.

8. Future Trends in AI and Network Orchestration

The acquisition, applicability, and analysis of data determine the output of intelligent software. Statistics, as a broad and abstract field, shines when tasked with making predictions about distributions over populations. The fault of innumerable predictions about any particular individual comes with the territory, and it is expected that many of them will be faulty. As the use of statistical models and machine learning spreads to new tasks, such as taking charge of cars or grading student essays, this expectation becomes disconcerting [14]. One consequence of AI systems designed using past assumptions is a desire for limited liability. Acknowledging that the choices made during the engineering of a statistical process might lead to disaster is acknowledging an enormous fault. But as these processes affect more people, these choices grow magnitudes more important. Those making them have a responsibility to consider the likely and unlikely pathways leading from their choices to a dangerous AI that could be tasked in a way capable of inflicting a great deal of harm.

9. Ethical Considerations in AI Deployment

Put simply, it is morally impermissible to make choices that would lead to a malicious outcome. This does not mean others want that choice. Inadvertent pathways leading to a dangerous AI can be difficult to foresee. This suggests those making choices ought to ensure they give careful consideration to their choices, as well as being clear about the assumptions, trade-offs, and choices they make during the process.

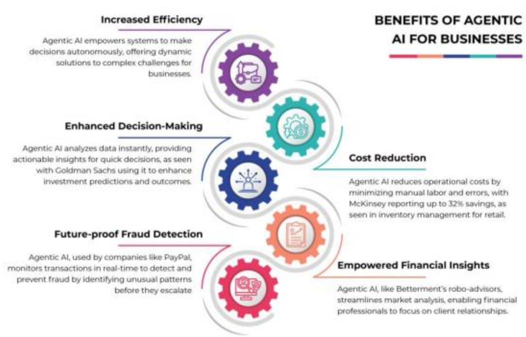

Fig 4: Agentic AI

9.1. Bias and Fairness

Machine learning algorithms rely on data input to make a decision. Since this data is a reflection of the society and the historical prejudice encumbrance, the results of the decision can easily be unintentionally discriminatory. In this section, basic ways how to detect bias and its possible solutions are presented. Bias detection can be divided into two categories. The first one are methods that require access to the training dataset. From the computational point of view, these techniques are the most straightforward. They usually focus on analysing the training dataset by detecting under- or overrepresentation of groups of individuals. The second category of bias detection methods is targeted at evaluating a black-box ML service for bias. These methods do not require access to the training dataset. They mimic consumer query input to the service on the interface level. Output labels are then collected and analysed for potential bias [15].

Bias detection can be seen at service consumption as a two-step top-level procedure. At first, focus on determining the most relevant attributes in regard to bias analysis. As this part is specific to the service in question, other parts will be omitted in this section. Once the attributes are identified, it is possible to proceed with the detection itself on a more general level [16]. Discrimination is defined as abnormal distribution of a labelled attribute from a baseline training-unbiased distribution p (y|x), i.e. a distribution learned by the training run of the service. The particular discrimination and its corresponding abnormality were defined in terms of statistical KL divergence. Eventually service query results should not be disregarded by the consumer. They may eventually contain helpful information about the service, like the model itself or its dataset bias. The potential of reverse engineering the model itself by querying the service in the black box will be further explored. It is very reasonable to expect that such a service will learn a p(y|x), with an implicit X that is directly observable. If the granting consumers access to the raw data, i.e. (x, y), this baseline distribution could be obtained directly.

9.2. Accountability in AI Decisions

As organizations increasingly use AI-based automation to help make decisions that are consequential and sensitive, accountability problem grows. AI-based decisions are potentially harmful when they cause concrete harms, whether to an individual (e.g. misclassification of as spam) or a broader social group (e.g. biased recruitment systems that exclude candidates as a function of similarity to successful hires based on historical data). AI decision-making tools can, or should, come with some accompanying rationale as to how this decision ultimately came to be. This rationale may be more or less interpretable, much like human awful decisions, but nonetheless it is typically hoped that such explanations will hold the tool, and/or its designers or users, accountable for its behaviour [17]. There is a multi-tiered, multi-actor landscape of accountabilities assumed with decision automation, with different processes and schemes for ensuring compliance and triggering potential consequences, with governance impacts at stake. For instance, the organization designing the tool would have some accountability to the organization deploying or using it,

10. Regulatory Frameworks for AI in Telecommunications

which in turn would be accountable to individuals or societal actors (citizens, lobby groups, regulators, etc.) impacted by its decisions [18]. Following a situative view of accountability, the basis of implicating agency is drawn from an examination of expectations and the surrounding machinery for holding to account when something unexpected occurs. The suggestion is that, adjusted for the radical differences in scale and context between human and AI agent societies, the accountability architecture for AI decision-making is little different from the mechanisms with regard to human agents. Nonetheless, this analogue supposition leads to detailed real-world implications for AI transparency and interpretability development efforts that directly address accountability concerns. It further motivates the consideration of other machinery that could be added in, beyond explanatory rationale.

11. The Interplay of AI and Human Oversight

The introduction of AI systems with agency is likely to have a significant impact on the workforce, requiring reskilling, upskilling, and skill replacement on an unprecedented scale. As AI systems become increasingly reliable and capable of agency in automated creative processes, workers' existing knowledge and skills may no longer be appropriate for their roles. Industries are likely to begin adopting such systems within the next five years, impacting millions of jobs worldwide [19]. Businesses, workers, unions, governments, and colleges and universities must prepare for this transition. Immediate measures are needed to mitigate the impacts. Worker groups must assess their industries and work to implement practical changes. Governments need to fund research to quantify the impact of agency AI, increase funding for retraining programs, and potentially tax companies that replace workers. Development of a skill replacement plan will ultimately depend on understanding the impacts of agency AI on different industries. Such examination requires academic input from disciplines including economics, sociology, and engineering, with long-term funding from federal agencies. Current efforts to better measure low-skill and wage labor markets may be inadequate, as these jobs may be at greater risk of mechanization.

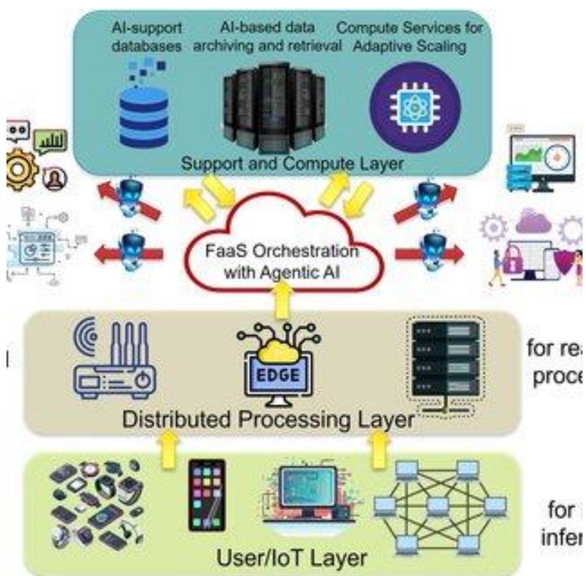

Fig 5: Advanced Architectures Integrated with Agentic AI

12. Impact on Workforce and Skills Development

Technical measures can be taken right now to mitigate the impacts of agency AI. The most immediate action is to set rigorous accuracy requirements for the deployment of agency AI in business. This includes establishing technical standards relevant to a given agency AI's abilities, which businesses must maintain if they wish to deploy such systems on a commercial basis, and creating regulatory bodies to audit businesses and performance claims. The data and parameters of agency AI must also be made publicly available. Such open-source practices will all but guarantee that worker groups can accurately understand the powers of AI systems before their deployment. Agencies responsible for modifying these standards and oversight must also be federally enacted and given power and resources to assist this transition. Such regulatory policies would ideally take the form of an expansion of the charter such that, for every novel application of agency AI, model architecture, dataset, training process, and performance must be made publicly available and open-source, with restrictions on commercial deployment that diminish with time and community reinforcement.

12.1. Evolving Job Roles

Inter-organizational network orchestration, manage complex optimization framework, autonomous, agentic AI, multi-agent systems, combinatorial optimization, intent-driven management, job roles, controllers, process control systems, network operators, supervisory systems, hierarchical, goals, pre-trained agents, machine learning, model-free, SARSA, off-policy, Q-learning, actor-critic agent-based approaches, traffic optimization, transfer learning.

The emergence of new paradigms for managing multi-domain, multi-layer networks, such as software-defined networking (SDN)/network function virtualization (NFV)-based control, provides a radical transformation of network management and orchestration (MANO). The application of these paradigms, however, also creates challenges that demand multi-deployment of distributed assets and services that require inter-organizational network orchestration. Supporting this new management layer, however, is a complex optimization framework that relies on agentic AI to completely transform the state of the art and create autonomous systems that understand goals and can offer orchestration services. Fully realizing this vision will take several years due to the inherent organizational structure of the telecommunications landscape, where operators are bounded by agreements. However, it is important to acknowledge that in the long run, nondiscriminatory access to connected and distributed networks will be essential and is aligned with key notions driving future internet architectures. This paper explores the new role of organizations, their controllers, and the competitive market environments in which these assets reside; the corresponding evolving job roles necessitated by this shift; and a coordinated but hierarchical approach to creating a layered intervention architecture and processes for delivering it .

$$\sum_{i=1}^{N} x_i \leq C \quad ; \quad x_i \geq 0$$

- x_i: resource allocated to agent i
- $U_i(x_i)$: utility function for agent i (e.g., throughput, latency)
- C: total available capacity (e.g., bandwidth)

Eqn.3: Network Utility Maximization

12.2. Training and Education Needs

Network operators deploy distributed and connected assets and services that, while being key inputs in the delivery of network services, cannot be completely unbundled. Because these assets and services are often operated on by distinct organizations, service providers and app developers must negotiate access and the specification and operations needed to ensure QoS. At the moment, inter-organizational negotiation generally takes the form of a partially serial process that can take time and be cumbersome. Decisions about edge computing in the context of competing or prioritizing service rollout may take a year to negotiate. Regarding distributed wireless systems that allow passive intervention, the allocation of fundamental spectrum resources is also expected to last months or be fraught with disputes. With autonomous coordination, the specification of intent and subsequent network function discovery, instantiation, composition, and management would be completely automated. Organizations could trade as sets of software agents competing on their delivery of QoS, and service developers could simply specify a description of the application or its intent in natural language.

13. Conclusion

The introduction of autonomous, self-operating networks is a critical aspect of advancements in telecommunications networks. The anticipated developments over the next several years will involve more sophisticated and intelligent network infrastructure and equipment, leading to a paradigm shift in telecommunications from a mindset of "managing and operating the network" to "setting the goals and objectives to the network." There are growing interests from academia and industry in both the research and development of agentic AI, which embody AI agents having the human-like agency capability of acting autonomously and goal-oriented. It is anticipated that the objectives to be utilized by user agentic AI will be expressed as "goals." As such, there is a need for enhanced methods for constructing, refining, and decomposing goals, especially by non-programmers. Furthermore, relating to the goal patterns and environments to goals constructed, there is a need for enhanced methods to define and match goal patterns to recognize a variety of goals and to customize agentic AI to better fit specific applications.

End-to-end synthetic AI training and education processes must be introduced to enable users to train generative training agents/capture users'/domains' intent with just a few example prompts. This applies to methods for the context generation process of the training and education processes. The generative training process is the core of the new paradigm of training, and the existing methods will need to be enhanced to allow performance, content, structure, and style control of generated content at various levels, including overall goals, constraints, and priming, within the context. This applies to the context elaboration and completion processes to help effectively treat different situations in the input data received from the user, which contain distinct key information and objectives concerning constructing different contexts. Finally, using an abstracted context as a guideline, there will be a need for enhanced methods for the output generation processes of individual agents to generate diverse output conforming to the goal information.

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