Machine Reasoning in FCAPS: Towards Enhanced Beyond 5G Network Management

Abdelkader Mekrache, *Member, IEEE,* Adlen Ksentini, *Senior Member, IEEE,* and Christos Verikoukis, *Senior Member, IEEE.*

***Abstract*—The increasing complexity of telecommunication networks has highlighted the need for robust network management frameworks. One such framework is FCAPS, which encompasses a wide range of functionalities, including fault management, configuration management, accounting management, performance management, and security management. To effectively address the complexities of modern networks, the integration of Artificial Intelligence (AI) techniques, particularly Machine Learning (ML) and Machine Reasoning (MR), has emerged as a pivotal strategy within FCAPS. ML provides networks with data-driven algorithms to recognize patterns and make informed predictions, while MR focuses on developing understandable AI systems that draw conclusions based on explicit knowledge. In this paper, we explore the field of MR and its usage within FCAPS. First, we present an overview of the FCAPS framework, including a categorization of FCAPS levels. Then, we provide a novel taxonomy of MR approaches, presenting both traditional and advanced MR. Next, we review MR techniques to address emerging concerns within FCAPS. Finally, we discuss open issues and future directions for further study toward 6G networks.**

***Index Terms*—Telecommunications, Network management, FCAPS, Machine Learning, Machine Reasoning, 6G networks.**

CONTENTS

A. Mekrache is with EURECOM, France (e-mail: abdelkader.mekrache@eurecom.fr).

A. Ksentini is with EURECOM, France (e-mail: adlen.ksentini@eurecom.fr).

C. Verikoukis is with ISI/ATH, University of Patras, Greece (e-mail: chverik@gmail.com).

List of Acronyms

1G	First-generation
5G	Fifth-generation
6G	Sixth-generation
A3C	Asynchronous Advantage Actor-Critic
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
API	Application Programming Interface
BAM	Bandwidth Allocation Model
BS	Base Station
CBR	Case-Based Reasoning
CIM	Common Information Model
CLI	Command Line Interface
CNNs	Convolutional Neural Networks
CoT	Chain of Thoughts
DAG	Directed Acyclic Graph
DBNs	Deep Bayesian Networks
DCR	Distributed Constraint Reasoning
DDPG	Deep Deterministic Policy Gradient
DL	Deep Learning
DNA	Deep Network Analyzer
DNNs	Deep Neural Networks
DoS	Denial of Service
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
ETSI	European Telecommunications Standards Institute
FCAPS	Fault, Configuration, Accounting, Performance, Security Management
FNNs	Fuzzy Neural Networks
GAN	Generative Adversial Network
GNNs	Graph Neural Networks
GOFAI	Good, Old-Fashioned AI
HetNets	Heterogeneous Networks
HMMs	Hidden Markov Models
IBN	Intent-Based Networking
IBNS	Intent-Based Networking System
IoT	Internet of Things
ISO	International Organization for Standardization
ITS	Intelligent Transportation Systems
KPIs	Key Performance Indicators
KQIs	Key Quality Indicators
LLMs	Large Language Models
LMs	Language Models
LSTM	Long Short-Term Memory
LTE	Long-Term Evolution
MDPs	Markov Decision Processes
ML	Machine Learning
MLNs	Markov Logic Networks
MR	Machine Reasoning
NFV	Network Function Virtualization
NILP	Neural Inductive Logic Programming
NLP	Natural Language Processing
NMLNs	Neural Markov Logic Networks
NMNs	Neural Module Networks
NR	New Radio
ONOS	Open Network Operating System
OSI	Open Systems Interconnection
OWL	Web Ontology Language
PGs	Policy Gradients
PPO	Proximal Policy Optimization
QoE	Quality of Experience
QoS	Quality of Service
R2L	Remote to User
RAN	Radio Access Network
RCA	Root Cause Analysis
RDF	Resource Description Framework
RL	Reinforcement Learning
RNNs	Recurrent Neural Networks
SAC	Soft Actor-Critic
SARSA	State–Action–Reward–State–Action
SDN	Software Defined Network
SLA	Service Level Agreement
SMO	Systems Management Overview
SMS	Short Message/Messaging Service
SON	Self-Organizing Networks
SQL	Structured Query Language
TD3	Twin Delayed Deep Deterministic Policy Gradient
TRPO	Trust Region Policy Optimization
TSN	Time-Sensitive Networking
U2R	User to Root
WMNs	Wireless Mesh Networks
WSNs	Wireless Sensor Networks
WWW	World Wide Web
XAI	eXplainable AI
ZSM	Zero-touch Service Management

I. Introduction

A. Context and Motivation

NEXT-generation networks are anticipated to be more complex and interconnected, involving a large number of devices and systems. Consequently, network management frameworks are becoming more crucial to ensure the effective management of these networks. FCAPS is a widely used network management framework, introduced by the International Organization for Standardization (ISO) in 1977 [1]. It includes five levels: fault management, configuration management, accounting management, performance management, and security management. Fault management focuses on detecting and resolving network faults, while configuration management controls and maintains network device configurations. Accounting management tracks resource usage for billing purposes, performance management optimizes network performance, and security management safeguards the network from unauthorized access and potential threats [2]. By utilizing the FCAPS framework, network administrators can systematically address issues, ensuring the network's stability, reliability, and security.

In recent years, Artificial Intelligence (AI)-based FCAPS methods have gained significant attention due to the increasing

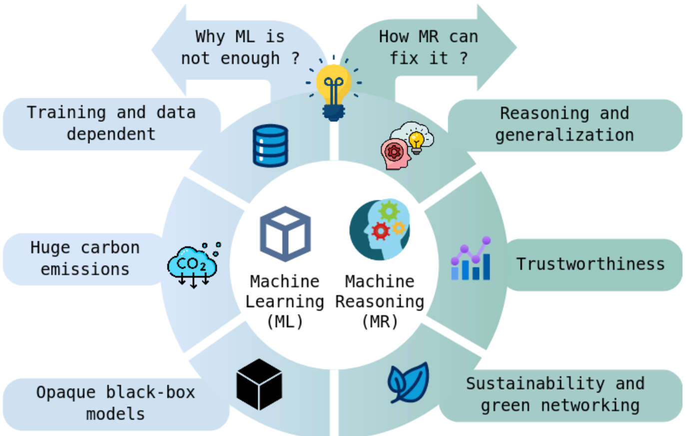

Fig. 1: Machine learning and reasoning paradigm [5].

complexity of modern networks. These approaches can be categorized into two distinct domains: Machine Learning (ML) and Machine Reasoning (MR). While both ML and MR are fundamental constituents of AI, they play distinctive roles in addressing complex issues and decision-making processes. On the one hand, ML focuses on developing algorithms and statistical models that enable computers to learn and improve performance on specific tasks without explicit programming. By analyzing vast amounts of data, machines can recognize patterns, relationships, and insights, empowering them to make predictions, classify information, and uncover hidden structures. ML has been successfully applied in various fields, including computer vision, medical diagnosis, search engines, speech recognition, and Natural Language Processing (NLP) [3]. On the other hand, the goal of MR is to develop AI systems that are understandable and can draw conclusions based on the information provided within specific limitations. While there may be slight variations in its “formal” definitions across various publications, MR methods typically share certain characteristics. Firstly, these systems rely on diverse types of knowledge, including logical rules, knowledge graphs, common sense, and textual evidence. Secondly, they utilize various inference algorithms to manipulate the available knowledge for problem-solving. Lastly, these systems are designed to provide clear explanations for their predictions, ensuring good interpretability [4]. Fig. 1 illustrates the paradigm of machine learning and reasoning within AI.

Traditional ML methods may not be efficient when exposed to unseen or new situations, while advanced neural network-based ML approaches lack explainability. These challenges make them less suited for managing networks where the environment is rapidly changing (e.g., the wireless channel is very unstable or network failure situations). Moreover, these methods need to be trusted to make granular decisions to manage advanced networks, which is not the case when using neural network-based ML methods. Consequently, one promising trajectory to explore is MR, as these methods have recently gained much interest from the research community and industry. MR approaches are explainable and capable of making decisions in new situations, given their ability to generalize and deduce novel scenarios and situations. Thus, as they are explainable, we can trust decisions made by MR, making them well-suited for network management frameworks. While MR has existed before, recent advancements in research are enhancing these approaches and applying them beyond 5G network management frameworks. These applications include fault management, configuration management, security management, and performance management, as they outperform ML in both results and explainability.

MR has revolutionized the telecommunications industry, delivering numerous benefits in terms of efficiency and innovation, particularly within the FCAPS framework. One of the most significant advantages is network optimization, achieved by analyzing vast amounts of network data. This allows MR algorithms to detect patterns and optimize configurations, leading to improved performance, enhanced reliability, and reduced downtime [6]. Moreover, MR plays a pivotal role in fault detection and predictive maintenance. By enabling proactive measures, it prevents network issues from escalating and minimizes service disruptions [7]. The automated troubleshooting capabilities of MR also significantly contribute to customer support, allowing rapid analysis of complaints and network data [8]. Another area where MR excels is in providing personalized services. Through the analysis of customer behavior and preferences, MR tailors offerings to individual needs, fostering customer loyalty and satisfaction [9]. Additionally, MR strengthens network security by swiftly identifying anomalies and cyber threats, enabling prompt responses to safeguard sensitive data [10]. MR can also be used to optimize resource allocation by leveraging demand patterns and traffic predictions. This can lead to cost reduction and increased operational efficiency [11].

B. Review of Existing Related Surveys

Several studies have already addressed some levels of the FCAPS framework for network management. For instance, in [12], the authors provided an overview of fault management in Software Defined Network (SDN), identifying main issues, surveying efforts to address them, and discussing tradeoffs in approaches for different scenarios. In addition, cell fault management approaches were surveyed in [13]. The researchers in this latter also discussed explainability, changes in network architecture’s impact on fault management, and future directions for research in this field. Similarly, ML-based network fault management was studied in [14]. Moreover, [15] delved into fault management in the realm of Network Function Virtualization (NFV). They proposed a comprehensive state-of-the-art of fault management techniques and addressed the impact of virtualization on fault management. Authors in [16] explored the application of both ML and MR approaches to fault management in Industry 4.0, specifically focusing on predictive maintenance. Furthermore, AI-based Root Cause Analysis (RCA) methods were surveyed in [17], which are considered as fault analysis methods at the fault management level. On the other hand, configuration management and performance management approaches were surveyed in [18, 19], respectively.

Besides, MR approaches were also discussed in many surveys. For example, [4] provided an overview of MR, its

TABLE I: Existing surveys on FCAPS, MR.

Works	F	C	A	P	S	MR	XAI	Contributions
[12]	✓							A survey on fault management approaches in SDN.
[13]	✓					✓		ML-based cell fault management techniques.
[14]	✓					✓		ML-based cell network management techniques.
[15]	✓					✓		Fault management approaches in NFVs.
[16]	✓					✓		ML and MR based fault management in Industry 4.0.
[17]	✓					✓		AI-based RCA techniques for network faults.
[18]		✓				✓		Reasoning techniques for configuration management.
[19]				✓		✓		Deep Reinforcement Learning (DRL)-based methods in vehicular networks.
[4]						✓		MR and neural MR, various frameworks, applications.
[20]						✓		knowledge-enhanced neural MR approaches.
[21]						✓		GNNs approaches and applications.
[22]						✓		GNNs techniques for knowledge graph completion.
[23]						✓		GNNs techniques for knowledge graph recommendation.
[24, 25, 26]						✓		Neuro-symbolic reasoning.
[27]						✓		Uncertainty modeling in probabilistic reasoning approaches.
[28]						✓		Commonsense reasoning approaches within NLP.
[29]						✓		Reasoning with LMs.
[30, 31]						✓		Reasoning with LLMs.
[5]						✓		MR in Next-Generation wireless networks.
[32]						✓	✓	MR explainability techniques.
This survey.	✔	✔		✔	✔	✔	✔	**MR and neural MR approaches for FCAPS.**

motivation, various frameworks, practical applications, and the trade-off between neural networks and MR for better interpretability. In addition, the authors of [20] presented a review of research works, which delve into advanced reasoning approaches in the context of knowledge-enhanced neural MR. Similarly, Graph Neural Networks (GNNs), which are a neural MR approach, were surveyed in [21]. The authors discussed the applications of GNNs across various domains and summarized the open source codes, benchmark data sets, and model evaluation of GNNs. In addition, GNNs for knowledge graph completion and recommendation were studied in [22, 23] where the authors presented the various strengths and weaknesses of the proposed methodology and tried to find new exciting research problems in this area that require further investigation. The works [24, 25, 26] provide surveys in the field of neuro-symbolic reasoning, where the integration of neural networks with symbolic reasoning has been investigated and analyzed. Meanwhile, researchers in [27] tackled uncertainty modeling in probabilistic reasoning approaches, and authors of [28] surveyed commonsense reasoning within NLP. In the latter, there have been surveys conducted on the topic of reasoning with Language Models (LMs) and Large Language Models (LLMs) approaches, as evidenced by recent works like [29, 30, 31]. These surveys offer valuable insights into the latest advancements and practical applications within this dynamically evolving domain. Furthermore, *Thomas et al.* [5] conducted a valuable work exploring the limitations of current foundational models, such as LLMs, and how 6G networks can leverage MR to enable advanced 6G use cases. Finally, the authors of [32] aim to offer a selective overview of MR explainability techniques and studies, particularly in the context of modern MR branches, to complement the current eXplainable AI (XAI) landscape.

Table I summarizes the key topics discussed in the aforementioned works and offers a comparative analysis of their contributions in relation to our research. This comparison serves to facilitate a clear understanding of the distinctive aspects that set our work apart from the existing state-of-the-art literature. Despite the availability of numerous survey papers addressing FCAPS and MR individually, there remains a notable gap in the literature where comprehensive surveys jointly investigate the realms of FCAPS and MR. Such surveys are crucial for effectively harnessing the potential of MR in the development of responsible, trustworthy, and transparent FCAPS frameworks. In addition, while various research papers discuss FCAPS in networking, such as [12, 13, 18, 14], none have explored MR in the broader FCAPS domain. Therefore, there is a need for a comprehensive survey that explores MR and its potential applications in shaping the future of network management frameworks. Our main objective is to uncover MR's potential applications in FCAPS and to present a road-map for developing efficient MR models for future 6G networks.

C. Main Contributions

The contributions of this paper can be summarized as follows:

- *An overview of the FCAPS framework:* In this section, we delve into each level of FCAPS, providing a detailed presentation of the FCAPS layers. We categorize them and define subcategories for each layer, offering readers insights into the main scopes where MR extensively contributes to the FCAPS literature.

- *Comprehensive tutorial on MR approaches:* This section provides a clear definition of MR technology, introduces a novel taxonomy for categorizing MR approaches effectively, and delves into the critical aspect of MR explainability, ensuring that readers gain a comprehensive understanding of MR approaches. This tutorial equips readers with a solid foundation on MR technology, making it accessible and informative.
- *Comprehensive survey of MR approaches for FCAPS:* This section surveys MR and neural MR approaches for FCAPS, emphasizing their practical applications and impact on network management. We explore diverse MR solutions and investigate how they reshape network management. We also cite and discuss recent MR works at the forefront of research in this field, providing insights into the latest developments.
- *Identifying promising research directions:* This section explores the future of network management, focusing on the use of MR to drive advancements in 6G networks. We present future directions and open issues in the domains of: reasoning in ZSM-enabled fault management, reasoning in Intent-driven configuration management to enable Intent-Based Networking (IBN), enhanced performance management with distributed reasoning, reasoning & Blockchain in security management, reasoning with LLMs. Through these discussions, we aim to set the foundation for a future where MR approaches make network management more efficient and effective.

D. Paper Organization

The paper is structured as follows: Section II provides an overview of the FCAPS framework. In Section III, a tutorial on MR techniques is presented. Following that, Section IV delves into the application of MR in FCAPS. Open issues and potential future directions are discussed in Section V. Lastly, Section VI concludes the paper. To facilitate easy reference, the *List of Acronyms*, containing abbreviations commonly used in this paper, is provided in alphabetical order on page 2.

II. FCAPS : An Overview

The FCAPS framework, introduced by ISO in 1977, has become widely accepted as an approach to network management [1]. The term FCAPS originated in the initial Working Drafts (N1719) of ISO 10040, the Open Systems Interconnection (OSI) Systems Management Overview (SMO) standard. Originally, there were plans to establish five separate protocol standards, each dedicated to a specific functional area. However, as initial experiences revealed significant similarities among these protocols, the ISO working group consolidated them into a single protocol covering all five areas. These areas include fault management, configuration management, accounting management, performance management, and security management, each comprising various subcategories. Drawing inspiration from [33], we have organized each area/level, as depicted in Fig. 2. In the following sections, we delve into the details of each level.

A. Fault Management

Fault management in network operations encompasses essential categories to maintain a stable and reliable network environment. The first category, *fault diagnosis*, involves fault detection/prediction, which continuously monitors the network to detect or predict abnormalities promptly, and fault isolation/localization, pinpointing the exact affected location [34]. The second category, *fault analysis*, includes fault correlation and analysis to examine patterns between multiple faults and RCA for in-depth investigations into underlying causes. Finally, the third category, *Fault resolution*, implements corrective actions based on RCA results to resolve issues effectively and prevent their recurrence, ensuring seamless network performance.

As an example, in the context of 5G network operations, *fault diagnosis* involves employing advanced monitoring tools like QoS monitoring systems. These tools continuously assess critical network parameters such as latency, throughput, and packet loss in real time. Predictive analytics algorithms analyze historical data to identify potential issues, such as device failures before they escalate. In *fault analysis*, consider a scenario where a service disruption occurs in a 5G network, such as device failures leading to increased latency. In this case, RCA examines the interplay between different network elements, such as RAN and core network components, and determines if the disruption originated from a specific RAN node or if it is related to core network processing. *Fault resolution* can swiftly rectify the issue across the network, such as replacing faulty devices and automated reconfiguration, in order to restore normal network behavior promptly.

B. Configuration Management

Configuration management within network operations encompasses crucial aspects aimed at maintaining a structured and optimized network setup. The first facet, *installation*, involves the setup of network components and devices, ensuring their proper integration and functionality within the network infrastructure. *Provisioning*, the second category, focuses on configuring resources and services to align with operational requirements, ensuring that network elements are provisioned and available as needed. *Service planning*, the third category, encompasses the strategizing and arrangement of services to meet business objectives and operational demands. This includes defining service parameters, specifications, and deployment guidelines. *Network planning*, the fourth aspect, involves designing the network architecture, layout, and topology to ensure optimal connectivity, scalability, and performance. The fifth category, *Status and control*, entails monitoring and maintaining the ongoing health of the network by tracking its current state, performance metrics, and operational status.

For example, during the *installation*, network administrators deploy routers, switches, and other hardware components according to the planned network architecture. This involves physical setup, cable connections, and initial configuration to ensure seamless integration. For *provisioning*, engineers configure additional resources such as bandwidth, virtual machines, or network interfaces to accommodate increased

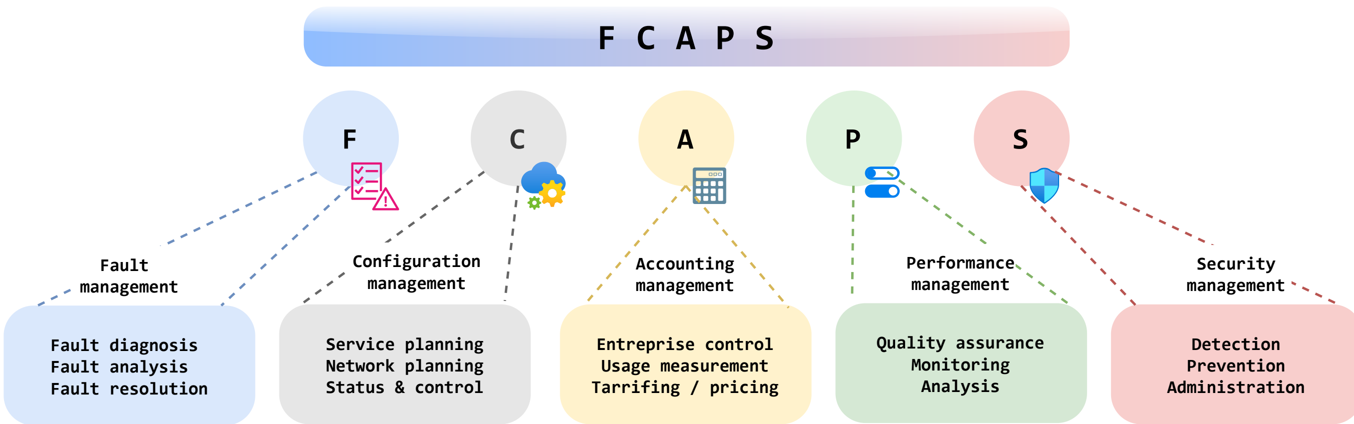

Fig. 2: Network management functions categorized using the FCAPS model.

demand, ensuring that the network can efficiently support new services without compromising existing ones. *Service planning* might involve network planners defining necessary service parameters, including bandwidth requirements, security protocols, and QoS policies, to ensure optimal performance and user experience. *Network planning* might involve network architects designing the network layout, ensuring connectivity, scalability, and performance while considering factors like data traffic patterns and potential points of failure. In *Status and control*, real-time network performance metrics tracking helps identify and promptly address configuration issues.

In section IV, we will focus our discussion on research contributions primarily within three categories: *Service planning*, *network planning*, and *status and control*. This focus is driven by the noticeable research gap surrounding the integration of MR in *installation* processes. As for *provisioning*, we will be featuring relevant works in the performance management subsection, as there exists a significant overlap between the two sections due to their shared emphasis on resource allocation.

C. Accounting Management

Accounting management involves tracking and monitoring resource usage on the network. It deals with gathering data related to user activities, resource consumption, and system performance. This information is crucial for billing purposes, capacity planning, and identifying potential resource bottlenecks or misuse. To the best of our knowledge, there are no works that use MR for accounting in telecommunications, since it is a domain where traditional statistical and data-driven approaches have been predominantly employed. However, the application of MR techniques has the potential to enhance accounting management by providing more sophisticated and automated analyses, enabling real-time decision-making, and improving the accuracy and efficiency of resource allocation and billing processes. Future research in this area could explore the integration of MR methods to optimize accounting management in modern networks.

D. Performance Management

Performance management in the context of networking involves a systematic approach to optimizing the efficiency and reliability of network infrastructure and services. This comprehensive process encompasses various categories. *Performance quality assurance* ensures that network components and services adhere to predefined standards, guaranteeing consistent and dependable performance. *Performance monitoring* involves the real-time observation of network activities, enabling the detection of anomalies and timely troubleshooting. *Performance analysis* entails examining network data to uncover patterns and insights, aiding in informed decisions about network enhancements and resource allocation. Together, these categories contribute to a well-managed network that delivers high-quality performance, continuous monitoring, and data-driven optimization.

For example, in the context of a 5G network, *performance quality assurance* involves ensuring that the network components, such as BS and core network elements, meet the specified 5G standards for latency, throughput, and reliability. This guarantees that the network delivers the expected high-speed and low-latency services to end users. In *performance monitoring*, real-time observation in a 5G network includes tracking critical metrics like network latency, packet loss, and device connectivity. This enables prompt detection of anomalies, such as increased latency, allowing for maintaining optimal network performance. Regarding *performance analysis* in a 5G network, administrators delve into network data to uncover patterns related to user behavior, device compatibility, and service usage. This analysis informs decisions on network enhancements, ensuring that resources are allocated efficiently to meet the specific demands of 5G applications and services.

E. Security Management

Security management in digital systems is structured around crucial categories that collectively ensure the safety and integrity of information. The first category, *detection*, involves proactively identifying potential security threats by monitoring the system behavior and network traffic. *Prevention* forms the second category, emphasizing the creation of barriers against unauthorized access through measures such as firewalls, access controls, and regular updates. The third category, *administration*, encompasses policy setting, user authentication, audits, and training to manage security protocols effectively. These categories collaboratively create a comprehensive security framework that safeguards against breaches and ensures robust protection.

As an illustrative example, within the *detection* category, continuous monitoring of network traffic identifies unusual patterns or malicious activities, allowing for the proactive identification of potential threats, such as Denial of Service (DoS) attacks. In the *prevention* category, measures may involve implementing firewalls and access controls in the network, effectively filtering incoming and outgoing traffic to prevent malicious entities from infiltrating the network. In the *administration* category, security policies may be set to control user access, defining permissions for specific information. Additionally, user authentication measures, including robust password policies and multi-factor authentication, enhance security by adding an extra layer of protection.

III. Machine Reasoning: A Tutorial

MR is a crucial field that empowers machines with human-like abilities for logical thinking, problem-solving, and decision-making. By advancing the capabilities of AI, MR drives progress across diverse domains and opens avenues for more intelligent and autonomous systems. In this section, we will explore the fundamental definition of MR as widely recognized within the research community. Subsequently, we will delve into a comprehensive taxonomy of various approaches employed in the field of MR. Finally, we will demonstrate the practical implementation and relevance of MR explainability.

A. Definitions

MR, as described in the state-of-the-art, encompasses several varied definitions. For instance, in his work [35], *Léon Bottou* proposed a compelling definition of MR as *"algebraically manipulating previously acquired knowledge to answer a new question"*. This definition includes first-order logical inference, probabilistic inference, and simpler manipulations commonly used in building extensive learning systems. Moreover, Authors of [4] defined MR as *"Machine Reasoning research aims to build interpretable AI systems that can solve problems or draw conclusions from what they are told (i.e., facts and observations) and already know (i.e., models, common sense and knowledge) under certain constraints."*. This definition emphasizes the crucial elements of MR, such as incorporating both factual information and pre-existing knowledge to arrive at solutions. Additionally, the mention of "certain constraints" indicates the importance of context and limitations in the reasoning process, which aligns well with the realistic scenarios in which AI systems operate. Furthermore, authors of [36] mention a passage to emphasize the role of reasoning in making accurate decisions, *"A decision based on wrong facts can have devastating effects. Thus, it is important to associate our decisions with some sort of proof. This proof is provided by our reasoning skills. Reasoning helps us to validate what we think is correct or wrong"*. From a telecommunications perspective, we define MR as

Machine Reasoning involves leveraging Artificial Intelligence and employing data analysis techniques to manipulate telecommunications knowledge data. Its primary objective is to comprehend and reason about telecommunication use cases, thereby facilitating the generation of informed and explainable decisions. Consequently, this enhances trustworthiness, contributing to the improvement of network operations and the overall intelligence of the network.

B. Machine Reasoning Approaches: A Taxonomy

Fig. 3 presents a comprehensive taxonomy of MR approaches. These approaches have evolved over time to encompass both traditional and neural-based methodologies. Traditional MR methods typically rely on symbolic logic and inference algorithms for knowledge representation and reasoning. These methods offer explainability but face challenges due to the combinatorial explosion in large symbolic spaces. On the other hand, the advent of Deep Learning (DL) has led to the emergence of neural MR, where neural networks are employed to tackle reasoning tasks. Neural MR approaches have shown remarkable promise in handling complex patterns and large-scale data, enabling more accurate and efficient reasoning. Next, we detailly delve into traditional and neural MR.

1) Traditional Machine Reasoning:: Traditional MR methods are rooted in symbolic logic and inference algorithms. These approaches have been the foundation of early AI systems and have found applications in various domains. Traditional MR methods can be categorized into three main categories: symbolic reasoning, probabilistic reasoning, and Reinforcement Learning (RL). Symbolic reasoning methods utilize symbolic logic and inference algorithms for knowledge representation and reasoning. However, they lack the ability to handle uncertainty in data. Probabilistic reasoning methods combine probability with symbolic logic to address uncertainty, but they face challenges due to the combinatorial explosion in large symbolic spaces. RL is a different paradigm, where an agent learns to make decisions through trial and error by interacting with an environment and receiving feedback in the form of rewards. We consider RL as an MR approach because it involves the agent learning to reason and make decisions in an environment based on the feedback, with the aim of maximizing cumulative rewards.

- *Symbolic reasoning:* Before the late 1980s, the dominant approach in the field of AI was known as Good, Old-Fashioned AI (GOFAI) or the symbolic approach. This method involved utilizing symbolic logic and inference algorithms to manipulate knowledge, enabling reasoning systems to handle various tasks [4]. This category includes: rule-based systems [37], logic programming [38], expert systems [39], Case-Based Reasoning (CBR) [40], fuzzy logic [41], and semantic web and ontologies [42].
  - Rule-based systems: This approach explicitly uses rules to derive conclusions or execute actions based on facts and conditions, making it a symbolic reasoning paradigm. Rule-based systems can be represented

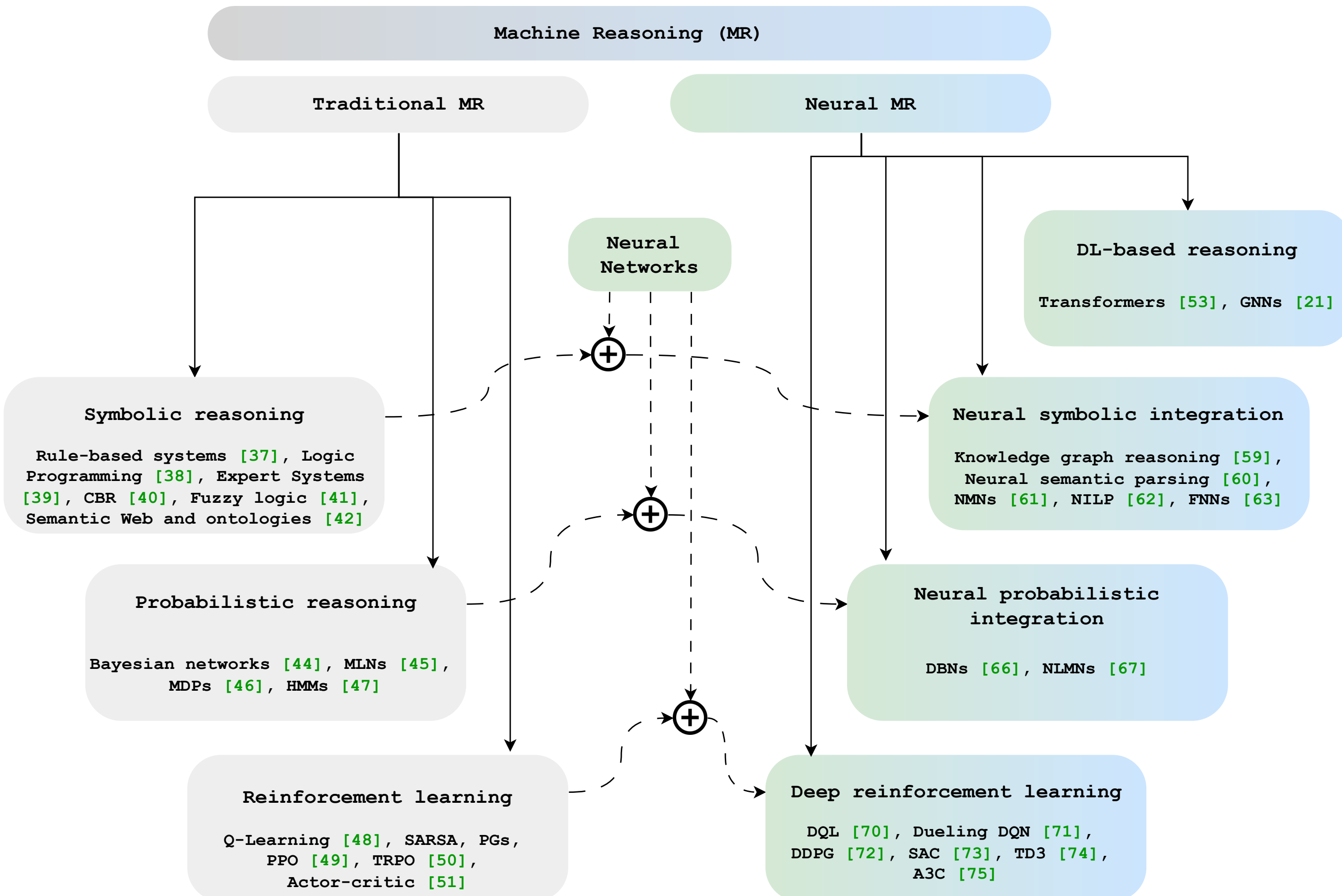

Fig. 3: Taxonomy of MR approaches.

using IF-THEN rules, where P represents a premise or condition, and Q represents a conclusion:

$$\text{IF } P \text{ THEN } Q \tag{1}$$

– Logic programming: Logic programming is another form of symbolic reasoning that uses logical rules and facts to derive conclusions. It is commonly used in languages like Prolog to perform deductive reasoning and infer new information based on the given knowledge base. In Prolog, logical rules are expressed using clauses. For example, a rule stating that a device is malicious:

$$malicious(X) : -device(X). \tag{2}$$

– Expert systems: Expert systems are typically rule-based, as they use a knowledge base containing symbols and rules (IF-THEN statements) to reason and make decisions based on human expert knowledge. An example rule:

$$\begin{aligned}&\text{IF (Symptom1 AND Symptom2)}\\&\text{THEN (Diagnosis)}\end{aligned} \tag{3}$$

– Case-Based Reasoning: CBR represents past cases as symbolic knowledge, and reasoning involves retrieving and adapting similar cases to solve new problems. Therefore, the principle of CBR is: Given a current problem, find the most similar past case(s) and adapt their solution(s) to the current problem context.

– Fuzzy logic: Fuzzy logic is a form of symbolic reasoning that uses linguistic variables and fuzzy sets to handle uncertainty and imprecision. Fuzzy logic rules typically take the form of “IF [fuzzy condition] THEN [fuzzy conclusion],” allowing for gradual transitions between true and false values. For example:

$$\begin{aligned}&\text{IF (Packet Loss is High)}\\&\text{THEN (Alert Severity is Critical)}\end{aligned} \tag{4}$$

– Semantic web and ontologies: The semantic web is an extension of the World Wide Web (WWW) that adds a layer of meaning to web content by utilizing symbolic representations such as Resource Description Framework (RDF) and Web Ontology Language (OWL). RDF employs triples consisting of subject, predicate, and object to express knowledge, while OWL allows for the creation of formal ontologies, specifying concepts, attributes, and relationships [43]. Ontologies provide a common vocabulary for sharing and representing knowledge, enabling interoperability. In this context, RDF and OWL enable knowledge representation and reasoning, allowing computers to not only store information but also make logical inferences and deductions based on ontological definitions.

While symbolic reasoning is effective in domains with well-defined rules and explicit knowledge representations, it may encounter difficulties in handling uncertainty and processing large-scale data. As a result, hybrid approaches combining symbolic reasoning with other AI paradigms have been proposed. For instance, probabilistic reasoning emerged as a solution to address uncertainty, and the integration of neural networks with symbolic reasoning was proposed to handle the challenge of processing vast amounts of data. These advancements offer a promising direction for overcoming the limitations of symbolic reasoning and creating more robust AI systems.

- *Probabilistic reasoning:* Probabilistic reasoning, as an alternative paradigm to traditional symbolic reasoning in AI, emerged as a response to the challenge of dealing with uncertainty. Unlike the deterministic nature of symbolic reasoning, probabilistic reasoning incorporates the concept of probability to handle situations where outcomes are uncertain or variable. Examples include Bayesian networks [44], Markov Logic Networks (MLNs) [45], Markov Decision Processes (MDPs) [46], and Hidden Markov Models (HMMs) [47], each providing distinctive techniques for modeling uncertainty and conducting probabilistic inferences.
  - Bayesian networks: These graphical models represent probabilistic relationships among variables using a Directed Acyclic Graph (DAG). In a Bayesian network, nodes in the graph represent variables, and directed edges between nodes depict probabilistic dependencies between them. For example, a network faults diagnosis system can be modeled using a Bayesian network with nodes for "Symptoms," "Fault," and "Root causes," where the directed edges between the nodes represent conditional probabilistic dependencies. Bayesian networks allow for probabilistic inference and updating of beliefs based on new evidence. This is accomplished through the application of Bayes' theorem, which can be expressed as:

$$P(X|E) = \frac{P(E|X) \cdot P(X)}{P(E)} \tag{5}$$

    In this equation, $P(X|E)$ represents the updated probability distribution of variable X given evidence E, $P(E|X)$ is the likelihood of observing evidence E given X, $P(X)$ is the prior probability of X, and $P(E)$ is the marginal probability of the evidence.
  - Markov Logic Networks: MLNs are a probabilistic logic framework that combines first-order logic and Markov networks. It enables probabilistic reasoning over complex, relational domains. In the graphical representation, nodes represent entities or variables, while edges depict probabilistic connections, each associated with a weight indicating relationship strength. The core equation in MLNs is:

$$w_1 \cdot f_1 + w_2 \cdot f_2 + \ldots + w_n \cdot f_n \Rightarrow \mathrm{s} \tag{6}$$

    Here, $f_1, f_2, \ldots, f_n$ are first-order logic clauses with associated weights $w_1, w_2, \ldots, w_n$. The formula represents a Markov network, where s signifies the strength of the relationship.
  - Markov Decision Processes: MDPs are used for decision-making under uncertainty, where transitions between states are governed by probabilities. The fundamental equation associated with MDPs is the Bellman equation, which expresses the optimal value function $V^*(s)$ for a given state s in terms of its expected immediate reward and the expected value function for the next state s':

$$V^*(s) = \max \Bigg[\sum P(s'|s,a) \\ (R(s'|s,a) + \gamma \cdot V^*(s')) \Bigg] \tag{7}$$

    In this equation, $P(s'|s,a)$ represents the probability of transitioning from state s to s' when taking action a, $R(s'|s,a)$ denotes the immediate reward received upon transitioning to s', and γ is a discount factor that captures the agent's preference for immediate rewards over future rewards. MDPs are frequently employed in RL to model and solve problems involving decision-making in uncertain environments.
  - Hidden Markov Models: HMMs are probabilistic models used for modeling sequences of observations, where the underlying state is hidden. The core concept in HMMs revolves around two fundamental equations: *(i)* State Transition Probability:

$$P(Q_t = q_i | Q_{t-1} = q_j) = a_{ij} \tag{8}$$

    Here, Q_t represents the hidden state at time t, q_i and q_j denote specific states, and a_{ij} signifies the probability of transitioning from state q_j to q_i. And *(ii)* Observation Probability:

$$P(O_t = o_k | Q_t = q_i) = b_{ik} \tag{9}$$

    In this equation, O_t stands for the observed data at time t, o_k represents specific observations, Q_t is the hidden state at time t, and b_{ik} indicates the probability of observing o_k when the system is in state q_i. HMMs combine these two concepts with an initial state distribution π to model sequences. They're used in various applications, like speech recognition (where hidden states represent phonemes) or in biology.

These powerful approaches have greatly enhanced AI systems' capabilities to reason and make decisions in complex and uncertain real-world scenarios. However, probabilistic reasoning has limitations due to computational expense, data requirements, and challenges in handling high-dimensional spaces and dependencies. To address these limitations, neural probabilistic integration leverages the strength of neural networks in learning complex patterns while incorporating probabilistic reasoning to handle uncertainty.

- *Reinforcement Learning:* RL, stands as a significant subdivision of ML, widely applied in academic works to tackle MDPs. An agent can learn its optimal policy π^* through interaction with its environment. At each timestamp t, the agent observes the state s_t of its environment and takes an action a_t, resulting in a new state s_{t+1} and receiving its immediate reward r_{t+1} as seen in Fig. 4. The observed information, i.e., the immediate

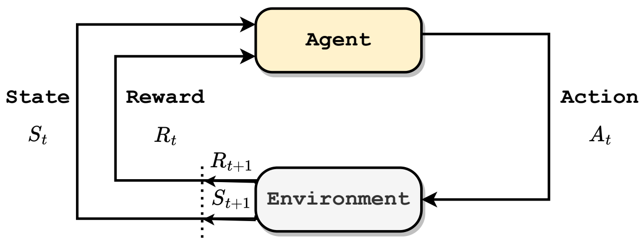

Fig. 4: Reinforcement Learning [19].

reward and new state, is used to adjust the agent's policy π, and this process will be repeated until the agent's policy approaches the optimal policy π^*, i.e., $\pi \rightarrow \pi^*$. This process of learning from experience and making decisions based on the estimated Q-value function aligns with the principles of MR, where the system uses past knowledge to make informed decisions. RL algorithms can be split into two main kinds of methods as shown in [19]. (i) methods based on value functions "value-based algorithms" and (ii) methods based on policy search "policy-based algorithms". There are also hybrid actor-critic approaches that employ both value functions and policy search.
  - Value-based RL: Estimates values of states or state-action pairs to maximize long-term rewards. Examples: Q-Learning [48], State–Action–Reward–State–Action (SARSA).
  - Policy-based RL: Learns the optimal policy directly without estimating value functions. Examples: Policy Gradients (PGs), Proximal Policy Optimization (PPO) [49], and Trust Region Policy Optimization (TRPO) [50].
  - Hybrid RL: Combines value-based and policy-based methods. Actor-critic is a common hybrid approach with an actor (policy) and a critic (value function). Examples: Actor critic methods [51].

  Modern networks, however, are large-scale and complex; thus, the computational complexity of the techniques quickly becomes unmanageable. As a result, to overcome the challenge, DRL has been developing to be an alternative solution.

Table II presents the pros and cons of each traditional MR approach. As explained in this table, traditional MR systems face limitations in handling computational complexity, especially in large-scale and complex modern networks. To overcome this challenge, Deep Learning (DL) was integrated with traditional MR to efficiently address high-dimensional and complex network optimization problems. Next, we present this class of methods called neural MR.

2) Neural Machine Reasoning: DL has achieved remarkable success across various domains, mainly attributed to Artificial Neural Networks (ANNs) [52]. ANNs have become a standard tool for data representation, simulating the functioning of the human brain through interconnected nodes. Each node's output is calculated using weights and a simple function based on input from neighboring nodes. Their flexibility, non-linearity, and data-driven model building make ANNs, especially DNNs, attractive inductive approaches. Neural MR encompasses several approaches that harness the power of neural networks and DL techniques for decision-making and problem-solving. These are categorized into four: DL-based MR, Neural Symbolic Integration, Neural Probabilistic Integration, and DRL. In the following, we delve into each category.

- *DL-based MR:* This category embraces transformer-based models [53] and GNNs [21].
  - Transformer-based models: Transformer-based models are attention-driven neural architectures used in NLP and sequential data tasks. These models exhibit a shallow level of reasoning on textual data but lack deeper reasoning abilities, positioning them as MR approaches. In order to enhance their reasoning capabilities, integration with symbolic knowledge or exploration of advanced positional encoding and attention mechanisms can be pursued [54]. Examples of their applications include: question answering (e.g., BERT, GPT) [55], language translation, and knowledge graph reasoning (e.g., TuckER) [56]. Furthermore, the research community has produced numerous surveys on reasoning with LLMs, such as [29, 31, 30]
  - Graph Neural Networks: GNNs are a class of DL models specifically designed for processing and analyzing graph-structured data. They excel in tasks that involve capturing intricate relationships, dependencies, and patterns within graphs. GNNs leverage techniques from neural networks to perform computations on the nodes and edges of a graph, enabling them to learn representations that encapsulate both the local and global information of the graph. This makes GNNs particularly suitable for a wide range of applications, including: node classification [57], recommendation systems [58], and knowledge graph completion [22].

  DL-based MR has significantly advanced the capabilities of AI systems in handling complex reasoning tasks. Transformer-based models excel in sequential data analysis, while GNNs are highly effective for reasoning over graph-structured data. The integration of these approaches has contributed to substantial progress in natural language

TABLE II: Pros and cons of traditional MR approaches.

Category	Approach	Pros	Cons
Symbolic reasoning	Rule-based systems [37]	Provide transparency and interpretability, allowing users to understand the decision-making process.	Struggle to handle situations outside their predefined rules.
	Logic Programming [38]	Facilitates concise and expressive problem-solving through formalized rules and relationships.	Encounter limitations in handling real-world complexities and dynamic scenarios.
	Expert Systems [39]	Capture and apply specialized knowledge for consistent decision-making.	Face challenges in adapting to dynamic situations and handling uncertainties.
	Case-Based Reasoning [40]	Utilizes past cases for flexible and context-aware problem-solving.	Struggle with unfamiliar situations and lack a structured knowledge representation, relying heavily on historical cases.
	Fuzzy Logic [41]	Allows for nuanced and flexible decision-making.	Require careful tuning of fuzzy sets and rules for optimal performance.
	Semantic Web [42]	Enhances data interoperability and knowledge representation.	Face implementation and adoption challenges.
	Overall	**Good at providing interpretable and trustworthy systems.**	**Faces challenges in handling uncertainty and changing environments.**
Probabilistic reasoning	Bayesian Networks [44]	Model probabilistic relationships for effective decision-making under uncertainty.	Requires accurate prior probabilities and may face complexity issues in scenarios with a large number of variables.
	MLNs [45]	Combine logic and probability for modeling complex relationships in a unified framework.	Face challenges in scalability and computational complexity due to the integration of logic and probability.
	MDPs [46]	Model dynamic decision-making under uncertainty.	Can be computationally intensive, especially in large state and action spaces.
	HMMs [47]	Efficiently model sequential data with hidden states, allowing for dynamic pattern recognition.	Face challenges in accurately estimating parameters and handling long-term dependencies in the data.
	Overall	**Good at handling uncertainty.**	**Faces challenges in handling high-dimensional environments.**
Reinforcement Learning	Value-based RL [48]	Estimates expected cumulative rewards through value functions, offering a solid foundation for decision-making	Encounter challenges in scenarios with high-dimensional state spaces.
	Policy-based RL [49, 50]	Directly learns the optimal policy without relying on value functions, providing flexibility in decision-making	Encounter challenges in scenarios with high-dimensional action spaces.
	Hybrid RL [51]	Integrates both value-based and policy-based approaches for improved decision-making	Requires careful design and tuning to balance the advantages of both approaches and face increased computational complexity.
	Overall	**Learns from the environment without requiring a dataset.**	**Faces challenges in handling large-scale environments.**
Overall	/	**Provides interpretable and explainable systems, efficient in decision-making.**	**Faces challenges in handling large-scale and complex networks.**

understanding, knowledge representation, and reasoning tasks, driving AI research towards more sophisticated reasoning and decision-making abilities.

- *Neural-Symbolic Integration:* Symbolic reasoning and probabilistic reasoning are traditional AI paradigms known for providing strong abstraction and generalization with good interpretability. However, their finite and discrete symbolic representations can make them fragile and inflexible [4]. To address these limitations, researchers have proposed neural-symbolic reasoning, integrating neural networks with symbolic reasoning. These approaches combine the benefits of both paradigms, leading to more robust and interpretable AI systems. By representing reasoning steps as differentiable modules, neural-symbolic reasoning allows for transparent and interpretable decision-making, bridging the gap between powerful learning capabilities and explicit reasoning in AI systems [25]. For instance, several approaches are considered as neural symbolic reasoning, such as: knowledge graph reasoning [59], neural semantic parsing [60], Neural Module Networks (NMNs) [61], Neural Inductive Logic Programming (NILP) [62], and Fuzzy Neural Networks (FNNs) [63].
  - Knowledge graph reasoning: Knowledge graph reasoning involves the integration of symbolic reasoning techniques with neural networks to perform logical inference over knowledge graphs. Knowledge graphs represent information as entities (nodes) and their relationships (edges) in a structured manner. The goal is to infer missing information or make predictions based on the existing knowledge. One common knowledge graph reasoning task is knowledge graph

completion, where the model predicts missing edges in the graph [59].

– Neural semantic parsing: Neural semantic parsing involves using neural networks to convert natural language sentences or queries into formal, executable representations, such as logical forms or programmatic expressions. This process enables machines to understand and execute commands or queries expressed in natural language [60].
– Neural Module Networks: NMNs use a modular architecture to perform reasoning tasks. Each module is designed to perform a specific reasoning operation or computation, and they can be combined in a sequence or graph structure to solve complex reasoning tasks. These modules can take different forms, such as Convolutional Neural Networks (CNNs) for image processing, Recurrent Neural Networks (RNNs) for sequential data, or attention mechanisms for focusing on relevant information [61].
– Neural Inductive Logic Programming: NILP combines neural networks with logic programming to learn symbolic rules from data. The neural network can learn representations of data, and logic programming algorithms can generate and refine logical rules from these representations [62].
– Fuzzy Neural Networks: FNNs are hybrid models that combine fuzzy logic and ANNs. They use fuzzy sets and rules to handle uncertainty and imprecision and neural networks to learn patterns and make predictions from data [63].

For a deeper exploration of technical aspects, the research community has produced comprehensive surveys on neural-symbolic reasoning. Interested individuals are encouraged to refer to the relevant literature [24, 25, 26, 64].

- *Neural-Probabilistic Integration:* These approaches aim to incorporate uncertainty modeling and probabilistic reasoning into neural networks, enabling AI systems to reason and make decisions under uncertainty. By representing uncertainty as probability distributions, neural probabilistic integration facilitates more robust and flexible decision-making in complex real-world scenarios [65]. Some approaches considered under neural probabilistic integration include Deep Bayesian Networks (DBNs) [66] and Neural Markov Logic Networks (NMLNs) [67].

  – Deep Bayesian Networks: DBNs are a powerful fusion of traditional Bayesian networks with DL architectures. These networks extend the capabilities of standard Bayesian networks by incorporating multiple layers of hidden variables and nonlinear transformations, allowing them to capture complex patterns in data. DBNs enable probabilistic reasoning and learning over high-dimensional and structured data, making them well-suited for tasks that require sophisticated probabilistic inference and modeling [66].
  – Neural Markov Logic Networks: NMLNs combine MLNs with neural networks to reason over structured and relational data. NMLNs can perform probabilistic inference and learning, making them suitable for complex reasoning tasks [67].

- *Deep Reinforcement Learning:* DRL stands as a progressive evolution of RL methodologies, first introduced by DeepMind in [68]. DRL harnesses the strength of DL to enhance the learning process within RL algorithms [69] as illustrated in Fig. 5. During real-time learning, the agent's gained experiences are stored and employed to train a neural network, subsequently empowering the agent to execute optimal real-time decision-making. In contrast to conventional DL methods, the neural network within DRL is continually updated with new experiences gained from interactions with the environment. Similar to RL, DRL is categorized into three distinct categories.

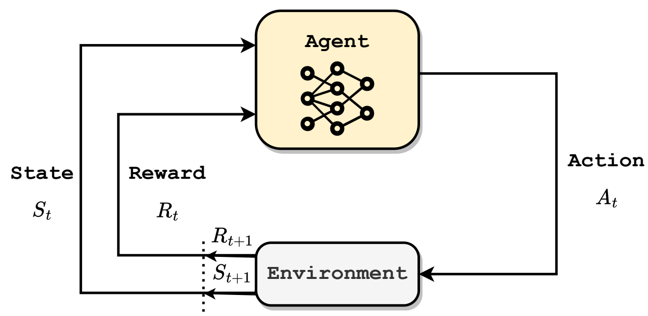

Fig. 5: Deep Reinforcement Learning.

  – Value-based DRL: Utilizes neural networks to approximate values of states or state-action pairs, aiding in maximizing long-term rewards. Examples include: Deep Q-Network (DQN) [70], Dueling DQN [71].
  – Policy-based DRL: Employs neural networks to directly approximate policies, enabling the agent to select actions that maximize cumulative rewards. Examples include: Deep Deterministic Policy Gradient (DDPG) [72], Soft Actor-Critic (SAC) [73].
  – Hybrid DRL: Combines neural networks to estimate both values and policies. Examples include: Twin Delayed Deep Deterministic Policy Gradient (TD3) [74], and Asynchronous Advantage Actor-Critic (A3C) [75].

Although neural MR effectively addresses the high-dimensional space challenges of traditional MR approaches, they are computationally complex and require a well-designed approach to be effective. In addition, using neural networks hides some interpretational capabilities of MR. Table III summarizes the pros and cons of each neural MR approach.

It is important to note that these categories are not rigidly separated; intersections and overlaps often exist among them. The landscape of AI research is ever-evolving, with researchers continuously pushing the boundaries of innovation. They are actively exploring novel avenues to seamlessly combine probabilistic modeling, neural networks, and symbolic reasoning, aiming to forge more sophisticated and powerful systems.

TABLE III: Pros and cons of neural MR approaches.

Category	Approach	Pros	Cons
DL-based MR	Transformer-based models [53]	Enables effective processing of sequential data through self-attention mechanisms.	Face challenges in handling structured knowledge representations and can be computationally demanding for certain applications.
	GNNs [21]	Capture complex relationships in graph-structured data.	Encounter challenges in scalability and generalization, particularly in large dynamic graph structures.
	Overall	**Effective in capturing complex relationships in knowledge data.**	**Can be computationally expensive for dynamic environments.**
Neural-Symbolic Integration	Knowledge graph reasoning [59]	Enables effective representation of complex relationships in structured data.	Pose computation complexity challenges, especially in large-sized graphs.
	Neural semantic parsing [60]	Facilitates automated conversion of natural language queries into structured representations.	Require substantial training data for optimal performance.
	NMNs [61]	Allow flexible reasoning over visual elements.	Demand thorough design for effective module interactions.
	NILP [62]	Use neural networks for enhanced learning and reasoning.	Could face challenges in handling large-scale structured data.
	FNNs [63]	Better handling of complex patterns compared to Fuzzy logic	Face challenges in interpreting the learned models.
	Overall	**Effectively address complex relationships.**	**Faces challenges in interpretation and requires a well-designed approach.**
Neural-Probabilistic Integration	DBNs [66]	Capture complex relationships and uncertainties in data.	Face challenges in training complexity, requiring substantial computational resources.
	NMLNs [67]	Enhance probabilistic reasoning through structured knowledge representation.	Encounter computation complexity in high-dimensional environments.
	Overall	**Effective in probabilistic modeling.**	**Encounters computation complexity in large-scale environments.**
Deep Reinforcement Learning	Value-based DRL [70, 71]	Adept at handling high-dimensional complexity.	May still be sensitive to hyperparameters.
	Policy-based DRL [72, 73]	Directly learns optimal policies, providing flexibility and tackling high-dimensional action spaces.	May require careful policy representation.
	Hybrid DRL [74, 75]	Integrates both value-based and policy-based approaches for a balanced decision-making strategy.	Require careful design and tuning.
	Overall	**Effectively tackling high-dimensional complexity.**	**Sensitivity to hyperparameters requires careful tuning.**
Overall	/	**Effective in handling high-dimensional and rapidly-changing environments.**	**Requires a carefully designed approach and involves computational complexity. Additionally, neural networks eliminate some interpretational capabilities of MR.**

Worth mentioning is the existence of various other taxonomies in the realm of MR, as evidenced by works such as [76, 64]. These contributions collectively underscore the dynamic nature of the field and the diverse approaches pursued to enhance the realm of reasoning systems.

C. Machine Reasoning Explainability

MR has gained significant interest due to the growing realization of ethical concerns, trust issues, and biases in AI decision-making processes. As complex DNNs become integral to various domains, the need to provide interpretable solutions for AI decisions is emphasized [77]. MR approaches in the realm of explainability have been extensively explored to shed light on the decision-making processes of MR-based systems. For instance, a comprehensive survey of MR explainability is presented by *Cyras et al.* in [32]. This survey covers the history and recent advancements of MR explainability, emphasizing recent progress. The paper categorized different branches of MR, including inference-based explanations, logic programming, and decision theory, and illustrates their contributions to XAI. The authors also classified MR explainability into three distinct groups: attributive, contrastive, and actionable. Attributive explanations explain the causal relationships between inputs, internal mechanisms, and outputs of AI systems, facilitating a deep understanding of the rationale behind outcomes. Contrastive explanations highlight the reasons for favoring one output over others, empowering users to comprehend the system's preferences and complexities. Actionable explanations represent a notable advancement, allowing users to intervene and collectively influence AI outcomes through concrete steps. These explanations address a wide range of user requirements and are in line with the fundamental goals of XAI, enhancing user understanding and interaction with AI systems. Importantly, the article highlights the dynamic nature of MR research within XAI, pointing to ongoing efforts to enhance and expand these approaches. Nevertheless, persistent challenges exist in MR explainability, particularly when dealing with uncertain or probabilistic information. Despite these challenges, the integration of MR into XAI plays a pivotal role in advancing interpretable and responsible AI systems[32]. Furthermore, authors of [78] delved into the realm of Knowledge Graphs and their associated technologies, introducing an additional dimension to XAI. They emphasize the intricate interconnection between explainability and advanced AI paradigms, highlighting the pivotal role played by Knowledge Graphs. This comprehensive perspective significantly advances the field of XAI and facilitates its seamless incorporation into the broader AI landscape.

IV. Machine Reasoning in FCAPS: A Survey

MR plays a pivotal role in network management beyond the 5G era. It enables essential tasks, including identifying root causes for issues and automating management processes. The subsequent subsections will offer a detailed explanation of research initiatives that leverage MR within each of the FCAPS levels.

A. Reasoning in Fault Management

1) Fault Diagnosis: *Fault diagnosis* is a crucial step in fault management as it allows for the detection of faults and failures. Traditional MR methods, including symbolic reasoning and probabilistic reasoning, have been widely explored in *fault diagnosis* literature. Symbolic reasoning methods were used in [7, 79, 80]. For instance, researchers in [7] proposed innovative fault assessment and fault prediction methods for Wireless Sensor Networks (WSNs). They focus on identifying and anticipating issues related to sensor resources, network bandwidth, and environmental conditions that may affect the system's performance. The fault assessment method is based on evidential reasoning, while fault prediction relies on a rule-based system. The experimental results indicate that the model can accurately estimate the current fault state of WSNs and make reliable predictions about future fault statuses. The authors in [79] introduced an innovative approach for automating anomaly detection and diagnosis in Self-Organizing Networks (SON) using CBR. They focus on detecting the degraded states within the managed network functions or other resources in the SON. Their method integrates inputs from human experts and advanced ML techniques in an iterative process. Furthermore, they demonstrated the potential benefits of adopting a more comprehensive perspective on mobile network self-healing, leading to enhanced performance. *Gomez et al.* in [80] proposed an automatic fuzzy-logic-based system to identify faults (i.e., service degradation within cells) in Long-Term Evolution (LTE) networks by defining linguistic rules and membership functions for symptom-fault relationships. Through this approach, the system achieves high fault identification success rates, addressing challenges in self-healing network design and leveraging historical data for fault detection. In addition, Probabilistic reasoning methods were used in [81, 82, 83]. For example, the authors of [81] designed a decision support system tool of general purpose based on the concept of using Bayesian networks for anomaly detection problems. The focus is on anomaly detection, specifically related to situations where there is a lack of information about all the possible values of the class variable (e.g., data about a reactor failure in a nuclear power station). Bayesian networks were also used for fault detection in [82]. The approach tackled issues in the vehicles data, including the open wireless medium, high-speed mobility, and vulnerability to environmental impact. The simulation results demonstrate that their proposed scheme exhibits superior fault detection and repairing accuracy, along with a lower false alarm rate when compared to existing methods. In [83], the authors proposed a HMMs-based approach for efficient cell outage detection in 5G Heterogeneous Networks (HetNets), achieving high accuracy in predicting Base Station (BS) states and cell outage detection. They classified 5G BS into four states and used HMMs to estimate cell outages probabilistically, demonstrating an average 80% accuracy in state prediction and 95% accuracy in cell outage detection through simulations on dense 5G HetNets.

On the other hand, neural MR were used intensely for *fault diagnosis*. For instance, the authors of [84] proposed a fault diagnosis scheme for telecom networks using GNNs. They utilized Long Short-Term Memory (LSTM) for clustering device states, followed by GNNs to diagnose faults and locate fault-root-devices. Moreover, authors of [85, 86] proposed a knowledge-guided fault localization method for optical networks, utilizing knowledge graphs and GNNs reasoning model to analyze network alarms and accurately locate faults. They implemented and verified the method on an Open Network Operating System (ONOS)-based software-defined optical networks platform, demonstrating high accuracy and highlighting the potential of knowledge graphs for alarm analysis and fault localization in large-scale optical networks. In [87], the researchers developed TraceAnomaly, an unsupervised anomaly detection system using ML and DBNs to detect trace anomalies in microservice invocation patterns accurately. TraceAnomaly outperformed existing approaches, achieving high recall and precision (both above 0.97) in detecting anomalies, surpassing the hard-coded rule approach by 19.6% and 7.1%, and seven other baselines by 57.0% and 41.6% on average, respectively. Moreover, researchers in [88] combined neural networks with rule-based systems in order to harness the strengths of both paradigms and detect anomalies like disruptions in communication services, signal degradation, and equipment malfunctions. This integration aimed to enhance fault diagnosis performance for advanced communication networks such as 5G and 6G. Furthermore, LLMs were used for logs fault anomaly diagnosis. For example, authors of [89] introduced LAnoBERT, a novel BERT-based unsupervised anomaly detection framework for log data that eliminates the need for log parsing. Anomalies here can encompass abnormal behaviors, errors, and intrusions within the system logs of a computer system. In addition, researchers in [90] delved into log-based anomaly detection challenges in production systems. They highlighted limitations in current techniques that rely on expert-labeled logs, proposing the exploration of MR like ChatGPT to improve anomaly classification in parallel file system logs.

2) Fault Analysis: Fault analysis, the essential second category of fault management, involves analyzing faults and detecting the root causes of failures. Conventional approaches like symbolic and probabilistic reasoning have been utilized in this context. For example, authors in [91] employed MR in the form of rule-based models for their NetRCA algorithm. The algorithm uses rule set learning, attribution models, and graph algorithms to enhance fault localization performance and interpretability. These techniques involve reasoning about relationships, patterns, and causal links within the network data to identify the root causes of faults. In addition, researchers of [92] utilized Bayesian networks to infer fault root causes in a distributed fault diagnosis framework for telecommunication networks. In their work, several public datasets were used for the evaluation, tackling multiple telecommunication failures' root causes, such as hardware failures. The Bayesian networks effectively handled uncertainty, supported reliable fault diagnosis, and ensured data privacy, as demonstrated through evaluation with benchmark datasets and real-world telecommunication network data. In their research paper [93], *Yang et al.* presented the Deep Network Analyzer (DNA), an Apache Spark-based big data analytics platform. The focus of this work is on finding associations between Key Performance Indicators (KPIs) and Key Quality Indicators (KQIs) in a cellular network to identify root causes behind KQIs performance degradation. DNA employs rule-based methods for RCA in mobile wireless networks. By mining association rules between anomalous key quality indicators and KPIs, DNA efficiently identifies the underlying root causes of network anomalies. In [94], the authors introduced an adaptive RCA approach utilizing Bayesian network theory for automated fault detection and diagnosis in cellular networks. Their approach is designed to identify notable deviations in cell performance from the expected profile values. The proposed solution aims to reduce faults, enhance efficiency, and facilitate self-healing mechanisms in LTE and emerging 5G networks. Moreover, researchers of [95] introduced an intelligent approach using the Bayesian networks model for RCA in communication networks. They focused on detecting and diagnosing faults, including fiber link breaks, equipment board faults, and communication network disruptions, in an optical transport network used by a railway company. By employing message propagation and a parameter storage system, the proposed framework enhances fault localization automation, providing a reliable and efficient solution for quick and accurate fault identification in communication networks.

On the other hand, neural-driven MR methods were introduced to address *fault analysis*. For example, researchers of [96] proposed a novel RCA framework that combines GNNs with graph structure learning to infer hidden dependencies and accurately identify malfunctioning machines or devices in 5G networks, even with incomplete data. Experimental results demonstrated higher accuracy in identifying root cause and victim nodes as the number of nodes in the network increased. Authors of [97] present an innovative approach for RCA and fault detection in telecommunication networks. The method employs data-driven techniques to associate alarms, extract root-derived graphs, and build alarm propagation graphs based on Bayesian network principles. Various root causes for alarms, such as device offline and failure of the board's overall function, are considered in this research. By utilizing GNNs, the approach learns the mapping between alarm propagation graphs and true faults. The goal is to address the limitations of rule-based methods and reduce the dependence on expert knowledge. The evaluation conducted in both offline and online environments of a real-world RAN demonstrates a noteworthy 4.6% improvement in F1-score compared to state-of-the-art approaches.

3) Fault Resolution: Fault resolution, the third and crucial category of fault management, involves taking corrective actions to address and resolve the root causes of failures detected during *fault analysis*. Both traditional and neural MR methods have been extensively explored in the literature. For instance, the authors of [98] introduced "DisCaRia," a distributed CBR system that assists administrators in resolving faults in communication networks and distributed systems. DisCaRia integrates various fault knowledge resources from the Internet and uses a distributed CBR approach based on scalable peer-to-peer technology. In addition, *Saeed et al.* in [99] developed a self-healing capability for wireless cellular networks, compensating failed cells using neighboring cells' antenna reconfiguration and power adjustments based on fuzzy logic control and RL. This approach improved network performance and ensured uninterrupted Quality of Experience (QoE) for users. In [100], the authors employed RL as a reasoning method for an automatic and self-organized approach to cell outage compensation in wireless cellular networks. The RL-based agents in enhanced node BSs dynamically adjust downlink transmission power and antenna tilt to optimize coverage and capacity, resulting in improved user recovery from outages compared to traditional resource allocation schemes.

Moreover, neural-based MR techniques were also employed for *fault resolution*. For instance, the authors of [101] proposed an automated solution for cell outage compensation in complex 5G networks using an DRL. This approach involves selecting neighboring BSs as compensation, constructing a problem model to maximize transmission rates while considering Quality of Service (QoS), and adapting BS parameters. In addition, *Shaghaghi et al.* in [102] presented a zero-touch, DRL-based proactive failure recovery framework for fault resolution in a virtualized network relying on the NFV concept. Using DRL with advanced algorithms, the framework predicts and addresses potential issues preemptively. They incorporate the age of information concept and employ a hybrid neural network architecture to enhance the framework's reasoning capabilities. This approach combines predictive modeling, MR, and neural networks to achieve automated and intelligent fault resolution.

B. Reasoning in Configuration Management

1) Service Planning: Service planning, a pivotal component within network configuration management, involves strategic decisions and arrangements to ensure that network services align with both business objectives and operational needs. Traditional MR methods were used in service planning for configuration management. For instance, researchers in [103] proposed an agent-based system for automation in network management within advanced mobile networks like 5G. The system utilizes performance management data reports, depicting scenarios like coverage problems, local overload, and mobile overload, accompanied by cell-level KPIs. Then, it employs both symbolic reasoning (semantic web and ontologies) and probabilistic reasoning (MLNs) to enable relatively simple software agents to address complex requests, ensuring efficient network operations. In addition, authors of [104] employed symbolic reasoning, utilizing the Common Information Model (CIM) and OWL ontology language, to enhance configuration management in Wireless Mesh Networks (WMNs). The system takes mesh router configurations as input, represented in a higher level of abstraction, enabling semantic checking, policy enforcement, and reasoning for WMNs nodes configuration. The framework supports persistence and web configuration interfaces, effectively addressing challenges posed by the distributed and dynamic nature of WMNs. Moreover, *Randles et al.* [105] introduced an ontology-driven framework to enhance autonomic network management by interpreting high-level goals or "intents" in closed control loops. Using semantic graphs and ontological modeling, their approach enables automated inference and understanding of relationships, strategies, and knowledge. By using network monitoring data as input to this framework, the system adapts and plans to satisfy and maintain intents, as exemplified by a real-life use case involving QoS assurance for a 5G Telecoms Network Slice.

2) Network Planning: Network planning entails the systematic design and expansion of network infrastructure to accommodate evolving demands while maintaining efficiency and scalability. Traditional approaches were employed in *network planning* for the configuration management, including symbolic and probabilistic reasoning. For example, authors in [106] presented an ontology-based approach that extends Time-Sensitive Networking (TSN) capabilities to support Plug-and-Play and automatic network configuration in the automotive domain. The ontology meta-models are designed to be used by automotive experts, such as network designers or engineers, to create concrete in-vehicle networks based on TSN, including the knowledge required for automatic configuration. By using the ontology, the system can reason about the network configuration and automatically configure the network to ensure deterministic behavior and support hard real-time communication with minimum latency based on Ethernet technology. To configure the network, the system utilizes TSN network knowledgebases, QoS requirements of applications, device information, and integration specifications to automate TSN network configuration. In addition, the authors of [107] introduced a significant advancement by integrating IEEE Time-Sensitive Networking (TSN) standards with Fifth-generation (5G) cellular networks, focusing on Industry 4.0 applications. They addressed the intricate task of dynamically adapting network configuration to maintain the desired quality levels for TSN traffic patterns. Their approach takes TSN information, including 5G QoS flow configuration, device location and context, KPIs, and relevant events such as network configuration actions, as input, enabling subsequent network reconfiguration. Leveraging an Automata Learning methodology characterized by rule-based symbolic reasoning, they successfully achieved real-time monitoring and adjustment of 5G QoS flows. Moreover, the framework proposed in [108] aims to configure firewalls for improved network security and functionality by integrating network topology and high-level behavior requirements. It takes as input network policies, expressed as high-level requirements, alongside network topology and a knowledge base. Then, it employs a rule-based system to derive precise low-level firewall configurations, ensuring alignment with specified communication rules. Predefined rules guide the system in generating consistent and conflict-free firewall settings that align with the network's structure and operational objectives.

Furthermore, the application of neural MR methods was utilized to improve *network planning*. For instance, authors introduced in [109] a parser framework based on neural semantic parsing techniques. This framework facilitates the tailored extraction of configuration details from network device manuals, leading to the creation of initial models. Through an extensive validation framework encompassing formal syntax and hierarchical validation, this approach using neural semantic parsing ensures the accuracy of the parsed models.

3) Status and Control: Status and control involve the immediate supervision and administration of network operations, facilitating rapid responses to incidents and maintaining stable and reliable service delivery. Conventional techniques were employed in the realm of *status and control* for configuration management. For instance, researchers in [110] employed a MLNs model integrated with an ontology and a graphical user interface for configuration management in a mobile network. They used a LTE simulator to generate KPIs data, such as channel quality indicator and radio link failures, which serves as evidence for the MLNs model. The MLNs model then reasons about configuration management parameters, such as transmission power and antenna angle (remote electrical tilt, RET), to optimize the mobile network's QoS and performance. Moreover, in [111], the authors presented a system that integrates a mobile network simulator, a MLNs model, and an OWL 2 ontology into a run-time environment for advanced automation in future mobile networks. The system takes into account the network context, analyzes uncertain information, and uses probabilistic reasoning to infer network configurations. The experimental platform demonstrates the value of semantic modeling and probabilistic reasoning in-network status characterization, optimization, and visualization, allowing for more efficient and reliable QoS in mobile networks.

C. Reasoning in Performance Management

1) Performance Quality Assurance: In the realm of performance management, *Performance quality assurance* emerges as a critical facet, ensuring that network services consistently meet or exceed the established performance standards and expectations. Traditional MR approaches were used in the literature to contribute to *Performance quality assurance*. For example, authors in [11] proposed a CBR approach for network slicing resource allocation in 5G RAN. The study treats the user distribution scenario as a case. It uses CBR to match new cases with cases stored in the library, finding similar cases to determine the best slice bandwidth ratio. The k-nearest neighbors algorithm is employed for retrieving similar cases, considering sparsity reduction and locality-preserving projections, demonstrating the effectiveness of the proposed architecture for efficient resource allocation. Moreover, in [6], the authors proposed a novel Bayesian cell selection/user association algorithm for 5G networks to achieve ultra-low latency and enhance system performance. By considering access node capabilities and user equipment traffic type, the algorithm maximizes the probability of proper association, leading to improved latency results. The simulation results demonstrate that the Bayesian game approach achieves the 5G low end-to-end latency target with a probability exceeding 80%.

Furthermore, neural MR approaches were also used for *Performance quality assurance*. For instance, in [112], researchers discussed 5G network concepts and the importance of resource allocation for different verticals. They implemented a DRL resource allocation module using DNNs to optimize QoS. The simulation results show improved resource allocation, leading to lower latency and better throughput compared to previous models. The authors of [113] introduced COUNSEL, a DRL-based framework designed to address resource configuration management challenges in Internet Clouds. COUNSEL efficiently manages dynamic workloads for multi-component services by offering three initial policies: over-provisioning, under-provisioning, and expert provisioning. Through its implementation, COUNSEL demonstrates consistent performance improvements with average rewards ranging between 20% to 60%, while meeting service level objectives and budget constraints. In addition, DRL was proposed in [114] to enhance 5G RAN intelligence and enable self-adaptation to the traffic pattern of the cell type. By monitoring Uplink and Downlink buffers, the proposed DRL algorithm derived the optimal Uplink/Downlink pattern in response to the current traffic configuration, ensuring timely and efficient delivery of the optimal RAN configuration.

2) Performance Monitoring: Performance monitoring stands as a pivotal pillar, offering real-time insights into the dynamic behavior of network systems and applications. In this context, the research community utilized traditional MR to enhance *performance monitoring*. For example, the authors in [115] proposed an end-to-end network performance management framework based on CBR, multi-agent integration, perfSONAR [1], and large-scale network flow monitoring. This framework aims to address the growing complexity and demands for high-performance network services in advanced data-intensive scientific research. It provides a systematic approach for detecting, diagnosing, and recovering ETE network performance issues. The framework was validated using real cases from a national research network in Korea.

Moreover, neural MR methodologies were employed. As an illustrative example, the authors of [116] analyzed various approaches for predicting Service Level Agreement (SLA) violations in cloud customer-provider service provisioning, emphasizing the utilization of network metrics and proposing a context-based model using GNNs. Their research demonstrates that the proposed GNNs-based model significantly enhances SLA violation prediction accuracy, holding potential significance for Cloud and Service providers. In Addition, researchers of [117] explored the potential of IBN for Intelligent Transportation Systems (ITS), leveraging DRL to optimize resource allocation in the context of 5G-enabled internet of connected vehicles. By jointly considering mobile network operator profits and users' QoE, they designed an intelligent traffic control system that dynamically coordinates edge computing and content caching, as demonstrated through real traffic data-driven experiments.

3) Performance Analysis: Performance analysis emerges as a pillar of network management, examining network data to uncover patterns and insights, thereby facilitating well-informed decisions regarding network enhancements and resource allocation. Within this domain, researchers have harnessed conventional methods of reasoning. For instance, authors in [118] introduced a novel cognitive network framework, termed FuzzOnto, designed to manage and optimize heterogeneous WMNs. By leveraging ontologies and fuzzy reasoning, this framework facilitates the dynamic incorporation of new network types and cross-layer parameters to enhance network performance. The primary contribution lies in its innovative approach to network optimization through semantic reasoning, demonstrated through simulation results that show up to a 70% improvement in network throughput compared to benchmark networks, spanning wireless mesh, LTE cellular, and vehicular ad hoc networks. The work in [119] addresses the challenges of managing complex HetNets such as Cloud, Internet of Things (IoT), vehicular, and multiprotocol label switching networks. They proposed and evaluated the use of CBR for cognitive management, specifically for Bandwidth Allocation Model (BAM) reconfiguration in these networks. The results indicate that CBR can learn from bandwidth request profiles and adaptively assist in BAM reconfiguration, leading to the self-configuration of BAM and optimized resource utilization. The authors of [120] proposed a predictive QoS mechanism called PreQoS that leverages Bayesian networks. The PreQoS mechanism is specifically designed for vehicle-to-everything services, which are critical in enabling safer and automated driving in the context of connected and automated mobility.

Additionally, neural MR techniques were utilized in various research publications. For example, in [121], the authors proposed a neuro-symbolic XAI twin system for ZSM in 6G wireless networks. For performance management, the system employs a neural-network-driven multivariate regression to analyze the time-dependent wireless internet of everything behavior and a DAG-based Bayesian network to infer symbolic reasoning scores. The XAI twin framework addresses extensible and modular management challenges and achieves around 96.26% accuracy with improved trust scores for reasoning and automation. Another noteworthy contribution is presented in [122], where XAI was integrated with DRL to explain

[1]https://www.perfsonar.net

decisions related to radio resource allocation in 6G networks. This integration enhanced decision robustness and algorithm performance by reducing model complexity and convergence time.

D. Reasoning in Security Management

1) Detection: Detection plays a pivotal role within the realm of security management, actively engaging in the identification of potential risks and vulnerabilities before they escalate into significant issues. The research community has put forth various traditional MR methodologies, including symbolic reasoning and probabilistic reasoning, to address this challenge. As an illustration, researchers in [10] conducted an in-depth exploration into jamming and intrusion detection for advanced networks such as 5G, aiming to detect intentional interference or disruption of wireless communication signals within a 5G network. Their study aimed to ensure reliability and prevent disruptions in critical applications. Their approach involved a fusion of Bayesian networks with supervised and unsupervised models, resulting in heightened real-time detection accuracy and effective handling of unknown jamming types. In another study, [123] also tackled the jamming detection problem within 5G networks by introducing an innovative strategy employing both ML techniques and Bayesian inference. By leveraging supervised learning models in conjunction with Bayesian network models, their methodology achieved impressive accuracy in jamming detection across diverse scenarios. They tackled jamming caused by various scenarios, focusing on classifying the frequency bands affected, including instances at 1.95 GHz, 2.14 GHz, and 3.49 GHz, as well as scenarios with no jamming signal present. Notably, this approach not only pinpointed the root causes of performance issues but also showcased its applicability in the context of 5G New Radio (NR) and Beyond-5G networks. Authors of [124] shed light on the limitations of conventional security intrusion detection methods when confronted with evolving cyber-attacks in power IoT-Cloud environments. To address this challenge, they proposed an intelligent response approach that revolves around access control guided by ontology reasoning and semantic web technologies. Security threats in power IoT-Cloud encompass internal system intrusion, network vulnerabilities, device vulnerabilities, malicious code infection, and information leakage. These threats are categorized into structural, physical, and external attacks. Structural attacks exploit architectural vulnerabilities, while physical attacks target source code weaknesses like Structured Query Language (SQL) injection. External attacks involve malicious programs such as Trojan horses and viruses.

Moreover, the field of security management has observed the incorporation of neural MR techniques aimed at *detection* purposes. For example, *Gao et al.* in [125] confronted the task of spam detection in rich communication suite messages (e.g., unwanted and unsolicited messages), a 5G application akin to multimedia-enhanced Short Message/Messaging Service (SMS). They introduced a multi-step approach involving the use of HMMs and CNNs. In [126], the focus is on tackling security obstacles in the evolving landscape of 5G networks. To this end, the authors propose an intrusion detection system using FNNs to counter potential security breaches and attacks within the network. Various types of cyber attacks have been addressed in this work, including , Remote to User (R2L), User to Root (U2R), and Probing attacks. Additionally, the paper specifically delves into the impact of varying membership functions and learning algorithms on enhancing the effectiveness of intrusion detection, emphasizing the importance of robust security measures in the context of 5G networks.In addition, the authors of [127] concentrated on enhancing the identification of Android malware in the context of 5G mobile IoT applications. With the growing menace of malware assaults on communication systems, the authors introduce a detection strategy that employs GNNs. By capturing the interconnections among various traffic attributes, GNNs aim to enhance the accuracy of malware detection. Furthermore, LLMs were harnessed in [128] to address the challenges of software vulnerability detection, resulting in the creation of SecureFalcon—an innovative model architecture built upon FalconLLM[2]. SecureFalcon demonstrated a remarkable 94% accuracy in distinguishing between vulnerable and non-vulnerable code samples, showcasing its potential to reshape software vulnerability detection methods in cybersecurity.

2) Prevention: Within the domain of security management, *prevention* stands as a cornerstone in the proactive mitigation of risks and vulnerabilities before they materialize into substantial threats. In this context, the research landscape has witnessed the emergence of diverse preventive methodologies using traditional MR. As an example, the work [129] envisions the 5G network as the fundamental architecture of the digital society, fostering innovative services and applications for devices, machines, and intelligent entities. The authors adeptly utilize fuzzy systems, along with other cognitive techniques like nonlinear systems, adaptive control, and AI, as part of their MR approach. This framework not only provides insights into forthcoming applications such as autonomous vehicles and robots but also accommodates varied forms of cognition, like edge and centralized cognition, tailored to specific latency thresholds. In a related context, *Vidal et al.* [130] tackled the dynamic landscape of 5G ecosystems and introduced an innovative framework for proactive self-protection. They introduced an architectural model, knowledge representation, and a rule-based reasoning strategy for countering cyber threats. Additionally, the authors propose a specialized prediction approach that anticipates the impact of DoS attacks in real communication scenarios. Addressing the vulnerabilities of 5G wireless communication networks, particularly in relation to security breaches like DoS attacks arising from small cell integration, researchers of [131] put forth a Bayesian game model. This model analyzes interactions between attackers and network defenders, deriving optimal defense strategies against attacks. Moreover, the authors presented an availability model grounded in a stochastic reward net aimed at mitigating network unavailability stemming from DoS attacks.

Moreover, the realm of security threat *prevention* has seen

[2]https://falconllm.tii.ae

the application of neural MR techniques. As exemplified by *He et al.* in [132], DRL is employed to enhance security protocols within mobile social networks. Through adaptive resource allocation and trust-informed decision-making, this strategy effectively mitigates potential security vulnerabilities.

3) Administration: In the realm of security management, *administration* plays a pivotal role in ensuring the effective implementation and orchestration of protective measures. Researchers have proposed traditional methods. For instance, the authors of [133] introduced a mathematical trust model for 5G telecommunication systems, evolving from earlier generations. It defines the core principle of trust and traces the trust model's evolution from 1G to 5G. Employing a graphical probabilistic model with Bayesian networks, the model facilitates the implementation of a trust center across the network to gather trust values from stakeholders and entities. In addition, the authors of [134] proposed a network security administration framework that integrates situational awareness, fuzzy reasoning, and role-based access control to address a diverse array of threats, including intrusions, malware, DoS attacks, data exfiltration, and phishing. Their work emphasizes real-time threat detection and identification through the use of a fuzzy reasoning algorithm, while role-based access control mechanisms enforce secure network administration by restricting user operations and implementing multi-level security concepts. Similarly, researchers in [135] incorporated fuzzy logic in proposing a novel privacy-preserving authentication framework for inter-vehicle communication networks, diverging from traditional architectures to leverage 5G and edge computing technologies. The authentication protocol, employing fuzzy logic for vehicle selection, ensures secure communication, identity privacy, and traceability with lower computational overhead compared to existing approaches. Also, researchers in [136] utilized a rule-based access control model to address the unique challenges of 5G architecture, emphasizing multi-tenancy, multi-domain, and multiple security levels. The proposed model allows specification and enforcement of actions and traffic types through an access control policy. The innovative model not only caters to 5G but also demonstrates scalability, making it adaptable to various architectures and capable of incorporating additional security features. Furthermore, the authors of [137] employed rule-based reasoning to dynamically apply QoS policies to security use cases in the 5G architecture. The proposed scheme utilizes predefined security indicators to trigger different policies, creating an efficient and responsive security enforcement schema. This rule-based approach ensures adaptability to security incidents, contributing to a unified and effective method for managing security within the network.

On the other hand, the research community has leveraged neural MR, which combines neural networks with reasoning methodologies. To give an illustrative example, authors of [138, 139] presented a solution framework for 5G security that integrates the physical and logical layers while prioritizing automated attack and defense strategies. This approach aims to tackle the dynamic security challenges of the 5G landscape by incorporating physical layer security within the overarching security framework, employing knowledge-based graph reasoning. Furthermore, the authors of [140] delved into the security challenges posed by the integration of 5G IoT into power systems. They proposed an administration strategy within security management by introducing an information security system based on ANNs and CBR system. They emphasize incorporating neuroscience-inspired algorithms to enhance security mechanisms and optimize data transmission paths. The multi-layered protection model includes a zero-trust security platform, network security logical isolation, and forward and backward isolation facilities to strengthen 5G IoT security in the smart grid.

E. Lessons Learned

In this sub-section, we delve into a comprehensive analysis of reasoning approaches employed at each level of the FCAPS framework. Subsequently, we offer valuable insights and comparisons to illuminate the efficacy of these approaches. Finally, we engage in an overarching discussion on using reasoning across the entire FCAPS framework, setting the stage for its application in the context of modern beyond 5G/6G networks. This latter prepares for a more in-depth exploration in section IV.

1) In Fault Management: In reviewing the literature mentioned earlier, a notable observation from the traditional reasoning perspective is the extensive use of symbolic reasoning, particularly in fault diagnosis and analysis. Traditional rule-based approaches, known for their effective performance, were prominently employed in these categories. Additionally, CBR approaches found application in diagnosis and resolution, leveraging insights and actions derived from similar past cases. These methods demonstrated efficacy in decision-making processes, especially in fault resolution scenarios. Probabilistic reasoning, exemplified by Bayesian networks, played a crucial role in diagnosis and analysis due to their capacity to handle uncertainty. This feature rendered them powerful tools for detecting and analyzing faults within complex systems. On the neural reasoning front, GNNs emerged as highly effective tools in fault diagnosis and analysis tasks. Conversely, in fault resolution, particularly in situations involving decisions to update configurations, DRL methods were extensively employed. Their effectiveness in addressing faults, especially in unforeseen scenarios, highlighted their significance in fault management. A noteworthy trend in neural reasoning approaches was the recent widespread utilization of LLMs in fault analysis, particularly when dealing with log files. LLMs demonstrated proficiency in comprehending human-like text found in log files, making them well-suited for fault detection in this context. Examining the research scopes, the literature showcased the application of fault management reasoning approaches across various domains, including , SON, cellular networks (LTE, 5G), HetNets, and NFV-enabled networks. Table IV provides a comprehensive summary of these works categorized by traditional and neural approaches, as well as by research scopes.

2) In Configuration Management: Upon reviewing the literature mentioned earlier, a notable observation emerges from the traditional reasoning standpoint, emphasizing the

TABLE IV: Fault management reasoning approaches.

Category	MR type	MR approach and research scope	Citations
Fault diagnosis	Traditional	Rule-based reasoning for fault prediction in WSNs.	[7]
		CBR-based anomaly detection in SON.	[79]
		Fuzzy-logic-based faults anomaly detection in LTE.	[80]
		Bayesian networks for faults anomaly detection.	[81, 82]
		HMMs-based cell outage detection in 5G HetNets.	[83]
	Neural	GNNs-based fault diagnosis.	[84, 85, 86]
		DBNs-based anomaly detection.	[87]
		Combining neural networks with rule-based for fault diagnosis.	[88]
		LLMs for log files anomaly detection.	[89, 90]
Fault analysis	Traditional	Rule-based models to identify the root causes of faults.	[91, 93]
		Bayesian networks-based RCA in networks.	[92, 94, 95]
	Neural	GNNs-based RCA and fault detection in 5G networks.	[96, 97]
Fault resolution	Traditional	Distributed CBR to resolve faults in communication networks.	[98]
		Fault resolution based on fuzzy logic control and RL.	[99]
		RL-based cell outage compensation in wireless cellular networks.	[100]
	Neural	DRL-based cell outage compensation in wireless cellular networks.	[101]
		DRL-based fault resolution in NFV-enabled networks.	[102]

TABLE V: Configuration management reasoning approaches.

Category	MR type	MR approach and research scope	Citations
Service planning	Traditional	Web ontologies and MLNs to ensure efficient network operations.	[103]
		Ontology-based frameworks to enhance configuration management.	[104, 105]
Network planning	Traditional	Ontology-based to support automatic network configuration.	[106]
		Rule-based approach to support automatic network configuration	[107, 108] .
	Neural	Neural semantic parsing to improve network planning.	[109]
Status and control	Traditional	MLNs model with ontology for configuration management in LTE.	[110, 111]

application of symbolic reasoning, particularly through web ontologies, in both service and network planning. Adopting ontology-driven frameworks proves pivotal, offering automation and reasoning capabilities for network configurations. This proves especially beneficial in navigating the intricacies of environments like 5G, facilitating efficient network operations. Incorporating ontologies or other semantic models facilitates higher-level reasoning, automated inference, and policy enforcement. Rule-based approaches also found significant utility in both service and network planning. Researchers integrated ontologies with probabilistic methods, such as , for status and control, enabling dynamic configuration adjustments to address evolving demands while maintaining desired service levels. Moreover, the introduction of neural semantic parsing has demonstrated its effectiveness in accurately extracting configuration details from device manuals. This advancement contributes to enhancing network planning, as exemplified by [109]. However, when compared to other FCAPS levels, reasoning in configuration management is relatively underutilized. A prospective approach to address this gap is the exploration of LLMs. Table V offers a comprehensive summary of the reviewed works, categorized by traditional and neural approaches as well as research scopes.

3) In Performance Management: Effective performance management plays a crucial role in ensuring the smooth operation and optimal functionality of network systems and applications. The surveyed literature offers valuable insights into the diverse reasoning approaches being utilized in this domain. Traditional reasoning methods, particularly CBR, have demonstrated their continued effectiveness across various facets of performance management, including quality assurance, monitoring, and analysis. Tasks like network slicing resource allocation and cell selection/user association benefit from the pattern-matching capabilities of CBR. Probabilistic reasoning, exemplified by Bayesian networks, has also proven useful in addressing network management challenges, such as predicting SLA violations and ensuring QoS. The recent surge in DRL has led to its adoption for decision-making in performance management, particularly in resource allocation scenarios within performance quality assurance and monitoring. However, researchers have also turned to XAI to understand and analyze the outputs of AI-based approaches in the domain of performance analysis. One approach involved combining symbolic reasoning with XAI to improve the understanding and interpretation of network performance. It's important to explore advanced XAI techniques, especially when combined with MR. This combination allows for a closed-

TABLE VI: Performance management reasoning approaches.

Category	MR type	MR approach and research scope	Citations
Performance quality assurance	Traditional	CBR approach for network slicing resource allocation in 5G RAN.	[11]
		Bayesian networks based cell selection/user association for 5G networks.	[6]
	Neural	DRL-based resource allocation to optimize QoS in 5G.	[112]
		DRL-based framework to address resource management challenges in Internet Clouds.	[113]
		DRL-based framework to derive the optimal Uplink/Downlink pattern.	[114]
Performance monitoring	Traditional	End-to-end network performance management framework based on CBR.	[115]
	Neural	Predict SLA violation with GNNs.	[116]
		DRL to optimize resource allocation for ITS.	[117]
Performance analysis	Traditional	Ontologies and fuzzy logic based to optimize heterogeneous WMNs.	[118]
		CBR for cognitive management in HetNets.	[119]
		Bayesian networks-based predictive QoS for ITS.	[120]
	Neural	Neuro-symbolic XAI twin system for ZSM in 6G networks.	[121]
		Combining DRL with XAI for 6G radio resource management.	[122]

loop understanding of the methods used in performance quality assurance and monitoring. A good example of this integration is presented in [122], where researchers employed DRL for performance quality assurance and used XAI to analyze the performance and decisions made by the DRL agent. Table VI provides a comprehensive summary of the reviewed works, organized by traditional and neural approaches, and further categorized based on research scopes.

4) In Security Management: The surveyed literature on security management offers valuable insights into the effectiveness of various reasoning approaches across different security domains. Traditional reasoning methods, such as fuzzy logic, Bayesian networks, and ontology reasoning, continue to demonstrate their effectiveness in various aspects of security management, including threat detection, prevention, and administration. A key takeaway is the value of integrating multiple reasoning models. For instance, combining fuzzy logic with cognitive techniques or neural networks with Bayesian models fosters a holistic and adaptive approach to evolving security challenges. Bayesian models, particularly Bayesian game models, showcase their strategic significance in devising optimal defense strategies against specific threats, like DoS attacks in 5G networks. The importance of explainability in security decisions is becoming increasingly evident, with the incorporation of XAI methods contributing to transparency and trust in decision-making. On the other hand, neural MR is being recently investigated within security management. The rapid rise and versatility of neural reasoning techniques, including LLMs, GNNs, and DRL, are undeniable. These techniques showcase their applicability in tasks ranging from software vulnerability detection to enhancing security protocols. Innovative synergies, like combining neural networks with traditional methods and incorporating interdisciplinary concepts like neuroscience-inspired algorithms, hold promise in creating adaptive and resilient security systems [140]. However, while the surveyed research demonstrates the potential of reasoning techniques in security management, there are limitations to consider. Traditional methods can be computationally expensive and less adaptable to dynamic environments, while neural techniques often require large amounts of data and may lack explainability. Future research should focus on addressing these limitations and exploring novel reasoning techniques that are efficient, adaptable, and transparent. Table VII provides a comprehensive summary of the reviewed works, categorized by traditional and neural approaches, further segmented based on research scopes.

5) In FCAPS: Reasoning within the FCAPS framework is crucial for making informed decisions, optimizing network operations, and ensuring the overall health and security of the network. Symbolic reasoning-based systems were very efficient in conventional network management systems. These methods are simple to design and allow easy interpretation of decision-making processes. However, symbolic reasoning-based systems face limitations in modern networks, such as challenges in handling uncertainty and the potential for combinatorial explosion when there are a large number of rules. Probabilistic reasoning and RL were implemented to address the uncertainty issues. These systems were also very efficient in conventional networks. However, networking is becoming increasingly complex with the explosion of beyond 5G network services. This results in a large number of devices that conventional approaches cannot handle. Currently, the research community is combining neural networks with traditional reasoning methods to implement modern reasoning approaches that are efficient and handle large amounts of devices. For example, DRL is being used in the context of decision-making, especially for resource allocation where there are a huge amount of devices and the system environment is complex. GNNs are also used extensively for graph reasoning to detect and resolve faults and anomalies. Additionally, advances in NLP are enabling the use of the reasoning abilities of LLMs in networking management systems.

TABLE VII: Security management reasoning approaches.

Category	MR type	MR approach and research scope	Citations
Detection	Traditional	Bayesian networks-based jamming and intrusion detection in 5G.	[10, 123]
		Ontology reasoning for security intrusion detection in IoT.	[124]
	Neural	Combining HMMs and CNNs for 5G intrusion detection.	[125]
		Intrusion detection system using FNNs in 5G networks.	[126]
		GNNs-based malware detection in IoT.	[127]
		LLMs-based software vulnerability detection using FalconLLM.	[128]
Prevention	Traditional	Fuzzy logic based threats prevention in 5G networks.	[129]
		Rule-based reasoning framework for proactive self-protection in 5G.	[130]
		Bayesian networks to derive optimal defense strategies against attacks.	[131]
	Neural	DRL-based approch to enhance security protocols within mobile social networks.	[132]
Administration	Traditional	Bayesian networks-based trust model for 5G telecommunication systems.	[133]
		Fuzzy logic-based network access control.	[134, 135]
		Rule-based network access control in 5G networks.	[136]
		Rule-based policy setting in 5G networks.	[137]
	Neural	GNNs-based to tackle the dynamic security challenges of the 5G.	[138, 139]
		Information security system based on ANNs and CBR system.	[140]

Nevertheless, the research community must invest more effort in designing novel reasoning approaches aligned with the requirements of modern 6G networks. These networks impose various constraints to support advanced use cases and applications. For instance, 6G networks are expected to perform closed-loop fault management, automatically detecting and resolving faults without human intervention, aligning with the zero-touch management principle. Reasoning is crucial for providing effective zero-touch management, especially in automatic closed-loop fault detection and resolution. Additionally, 6G networks are envisioned as intent-driven networks, where reasoning can play a vital role in designing intent-driven networking for configuration management. Furthermore, 6G necessitates improved performance management through distributed computations, prompting exploration of distributed reasoning methods. Finally, implementing diverse use cases in 6G networks requires robust security measures, leading to integrating tools like Blockchain for security management. Combining reasoning with Blockchain is an emerging research area that warrants further investigation. In the upcoming section, we will explore open issues and future research directions related to integrating reasoning to perform FCAPS in modern 6G network concepts. These include zero-touch fault management, intent-driven configuration management, distributed performance management, and security management with Blockchain. Furthermore, exploring reasoning with LLMs, given their prominence in current research activities, will be addressed for potential application across all FCAPS layers, leveraging the reasoning abilities and general knowledge of these approaches.

V. Open Issues and Future Directions towards 6G

In this section, we envision unexplored horizons and potential advancements within the realm of MR integrated into the FCAPS framework. As illustrated in Fig. 6, we discuss the following key areas:

- *Reasoning in ZSM-enabled fault management:* 6G networks aim to implement closed-loop fault management, automatically detecting and resolving issues without human intervention. Enabling such capabilities aligns with the ZSM vision, where network operations are fully automated. This sub-section explores how MR can play a crucial role in achieving this vision.
- *Reasoning in Intent-driven configuration management:* Simplifying configuration management for network operators is a key goal of IBN, a vital pillar in 6G networks. MR shows promise in enhancing IBN by providing intelligent solutions that "understand" and reason about user intent. This section explores how MR can be used to automate network operations and management by developing IBN solutions with a deeper comprehension of user intents.
- *Enhanced performance management with distributed reasoning:* 6G networks promise massive computational power for demanding use cases achieved through distributed computing. This is crucial for enhanced performance management. As a result, distributed reasoning is poised to become a hot topic in 6G research. This sub-section explores how MR can effectively distribute across multiple network nodes, scaling its capabilities and boosting performance.
- *Reasoning & Blockchain in security management:* Evolving security frameworks in 6G networks leverage advanced technologies like Blockchain, known for their robustness and effectiveness in demanding use cases. This sub-section explores the potential of combining MR and Blockchain to create more secure and reliable communication networks.

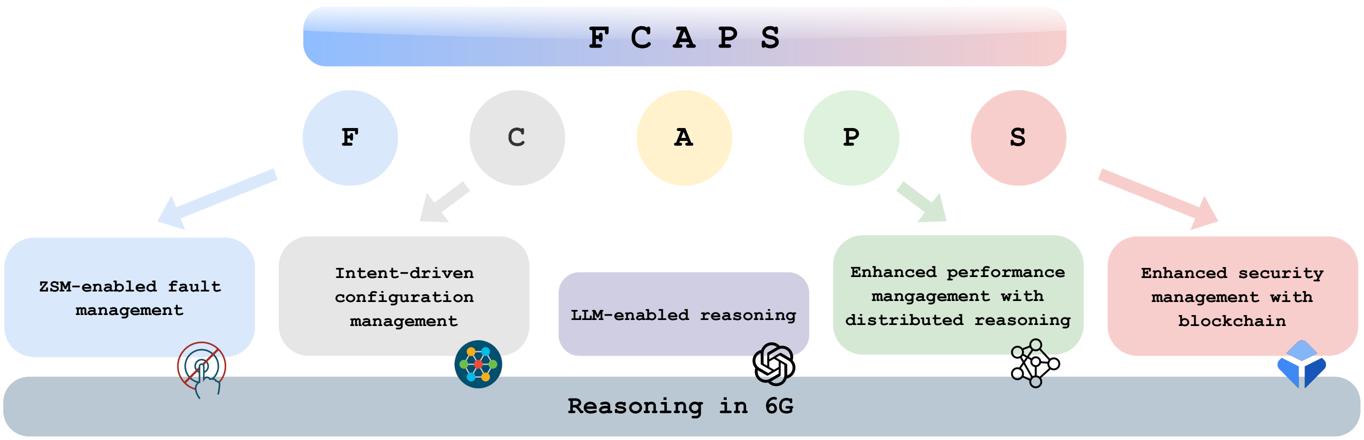

Fig. 6: FCAPS framework directions towards 6G.

- *Reasoning with LLMs:* Witnessing the explosion of LLMs and their impressive results across diverse fields, including 6G networks, we explore how MR can leverage this power. This sub-section delves into the potential of leveraging reasoning with LLMs to make intelligent decisions in 6G networks, ultimately shaping their future landscape.

A. Reasoning in ZSM-enabled Fault Management

The concept of ZSM has gained traction due to the increasing complexities arising from the surge in smart IoT devices and the demand for business-oriented services in 5G and beyond networks [141]. It aims to automate and streamline network operations, such as planning, deployment, and optimization, enhancing efficiency and reducing human intervention [142]. Recently, the European Telecommunications Standards Institute (ETSI) has launched two groups, zero-touch service management, and experiential networked intelligence, aiming to use AI, including ML and MR, to realize agile, fully automated management and orchestration of network resources [143]. These efforts align with the goals of ZSM, as they focus on leveraging advanced AI techniques to achieve autonomous network management, aligning with the increasing complexity and demands of modern network environments. Numerous studies have contributed to the utilization of ML to realize network automation under the framework of ZSM [144, 145, 146]. Consequently, there is an increasing demand within the research community to delve into MR-driven approaches in order to fulfill the objectives of ZSM.

ZSM offer significant benefits, such as reduced error rates and efficient handling of complex technologies. However, their management can be challenging, especially in heterogeneous and large-scale networks. Rule-based automated tools can be inflexible and error-prone, mainly when dealing with unforeseen situations or unexpected changes in the network environment [142]. Neural-based MR can help to address these challenges by enhancing decision-making and automation in network management. MR can learn from historical data to identify patterns that are difficult to capture with rule-based systems, such as the relationships between different network elements and the impact of changes to one element on the rest of the network [147]. Despite its potential, ZSM faces several limitations. First, accurate and up-to-date data is crucial for effective MR in ZSM. However, ensuring the quality and availability of data from diverse heterogeneous sources in ZSM can be challenging. Second, AI decision-making can be opaque, which can impede human comprehension and trust. One way to address this limitation is to integrate XAI strategies with MR. These strategies can provide insights into the rationale behind MR decisions, making them more transparent and accountable [148]. Third, ZSM systems must also address data protection concerns. This includes safeguarding management data, data integrity, service management, infrastructure functions, and resources [142]. Joint MR and Blockchain technology can provide a secure mechanism for storing and managing data, which could significantly enhance the management of security data for ZSM [149]. Fourth, integrating MR into existing ZSM systems and workflows can be challenging. It requires interoperability with legacy systems, APIs, and data sources. New techniques are needed to integrate reasoning-based strategies with ZSM systems in a scalable and efficient way [5].

B. Reasoning in Intent-driven Configuration Management

IBN is a groundbreaking concept that introduces a user-centric approach to network management [150]. It aims to revolutionize network management by prioritizing user intent and creating a dynamic, adaptable network ecosystem [151]. Although IBN is a relatively new term and technology, significant efforts have been dedicated to defining and standardizing it. It involves five essential steps: intent profiling, translation, resolution, activation, and assurance [152]. *(i)* Intent profiling is the initial stage where users interact with the Intent-Based Networking System (IBNS) to express their network-related desires. In contrast to traditional Command Line Interface (CLI) commands or complex Application Programming Interface (API) requests, the intent is conveyed in a human-friendly manner, utilizing natural language expressions or intuitive interfaces. *(ii)* Intent translation within the IBNS involves the transformation of a submitted intent into a network policy.

Subsequently, this network policy is translated into granular low-level configurations capable of being deployed to network devices. *(iii)* Intent resolution addresses potential conflicts arising from multiple users or groups submitting their intents simultaneously. The IBNS proposes conflict resolution strategies and alerts users or administrators when conflicts cannot be resolved feasibly. *(iv)* Intent activation proceeds once the IBNS confirms that deploying a new intent won't adversely affect ongoing ones. The IBNS then deploys the requested service, tailoring each intent to match users' personalized needs. *(v)* Intent assurance ensures the ongoing fulfillment of the intent throughout its life-cycle. By taking both proactive and reactive measures, it ensures the network aligns with the users' desires and facilitates self-configuration and self-healing.

Various research studies have explored the use of MR in IBNS. For instance, *Massa et al.* [153] introduced a logic programming-based approach for intent modeling and translation in IBNS, focusing on provisioning NFV chains. This approach can be extended to closed-loop management by enhancing the model to implement intent activation and assurance using advanced MR methods. Similarly, *Khan et al.* [154] utilized a Generative Adversial Network (GAN) to generate synthetic service graphs and a DRL mechanism for optimized graph selection. These techniques automatically translate high-level user requirements into service graphs, addressing the complex task of mapping user intents to network service structures. However, expanding the scope of business domains within an IBNS results in longer training times and increased waiting times for intent deployment. To mitigate this, leveraging the latest advancements in LLMs can streamline intent translation by enhancing generic LLMs using few-shot learning [155] or fine-tuning [156]. Furthermore, despite recent ML-based conflict resolution approaches in IBNS [157], there is a need for intent negotiation modules [158]. While frameworks for intent negotiation systems have been proposed, both generic [159] and platform-dependent [160], they are in the early stages of development and require further research. Investigating advanced MR systems in this area is crucial, given their promising results in conflict resolution in other domains [161]. For intent activation and assurance, the MR-based methods in the performance management subsection offer valuable insights. For instance, [116] demonstrated a composite SLA prediction model using GNNs, enhancing accuracy in predicting SLA violations. Additionally, [117] developed an intent-based traffic control system for ITS using DRL, orchestrating edge computing and content caching dynamically. However, these solutions face efficiency challenges in large-scale networks, especially with the advent of 6G networks supporting numerous applications with diverse QoS requirements. Hence, there is a need for advanced neural MR approaches in fully closed-loop IBNS scenarios, driven by the demand of modern networks and their heterogeneous applications.

C. Enhanced Performance Management with Distributed Reasoning

Distributed systems represent a paradigm shift in computer network design and management, enabling unprecedented scalability, fault tolerance, and efficiency through the power of decentralization. The research community in this domain is actively exploring novel approaches to address the challenges of distributed systems, collaborating on groundbreaking projects that push the boundaries of network design and management. In this realm of MR, some research works in the literature have investigated distributed approaches. For instance, authors of [162] focused on investigating the application of Distributed Constraint Reasoning (DCR) techniques in modeling and solving the distributed load balancing problem in edge computing scenarios. This work gives valuable insights into how DCR algorithms can effectively address the challenges posed by the growing number of IoT and mobile devices, ultimately enhancing the performance and efficiency of edge computing systems. Moreover, in [163], researchers have devised a distributed implementation of reasoning techniques to address the crucial requirement of handling extensive qualitative spatial and temporal datasets. Their approach demonstrates its effectiveness in managing networks with millions of relations, particularly in edge computing scenarios. Additionally, in the study presented in [164], the authors have developed a distributed approach for contextualized reasoning within multi-agent systems, tackling the challenges posed by incomplete and uncertain knowledge. Furthermore, In [165], the authors explored the integration of edge computing and federated learning to address the challenges posed by IoT-generated data at the network edge, enabling localized data processing and decentralized MR.

However, distributed reasoning in the context of multi-edge networks poses significant challenges in network management, including seamless integration with existing frameworks like FCAPS, handling the computational complexity of advanced neural MR approaches, and ensuring data security and integrity despite increased data exchange and cyber threats. To address these issues, it is crucial to develop distributed reasoning systems that utilize standard network protocols, employ distributed computing techniques to mitigate the complexity of advanced MR approaches, and implement robust security measures like encryption and blockchain [166]. By overcoming these challenges, the potential benefits of distributed reasoning can be harnessed to create resilient, efficient, and secure network management solutions, transforming network environments to meet the demands of the modern era.

D. Reasoning & Blockchain in Security Management

Trust is a pervasive concept in the expansive landscape of communication and networking, encompassing diverse domains such as AI, telecommunication, social network analysis, and cybersecurity [167]. Trust manifests as an acceptance level among network entities, a reliance on prior performance evaluations, and quantifiable confidence in an entity's ability to fulfill responsibilities within the network environment. As modern networks continue to evolve, ensuring trust becomes paramount to enabling efficient and secure interactions among diverse components. In this context, emerging technologies that enable trust become important, and Blockchain stands out as a particularly promising solution. Blockchain, characterized as a distributed and immutable digital ledger, operates transparently among interconnected peers. Comprising interconnected blocks, it records transactions and interactions among participants within a decentralized network. Each block contains transaction details and asset exchanges, while smart contracts enable self-executing codes verifying predefined conditions [168]. The potential of Blockchain extends to addressing pivotal challenges in the integration of AI with 5G networks. While AI, encompassing both ML and MR, can enhance network performance and security, its centralized nature exposes collected data to security threats. Blockchain's secure and shared ledger offers a solution by storing networking-generated data in real-time, ensuring anonymity through homomorphic encryption, and enabling AI to perform learning algorithms for network optimization and error prediction [169]. Moreover, the concept of decentralized AI, empowered by Blockchain, can autonomously execute tasks like network planning and optimization, enhancing network performance and security without third-party intervention. The convergence of Blockchain and AI, spanning ML and MR, is pivotal for achieving a truly smart and optimized beyond 5G networks, addressing both security and performance concerns [170].

In some recent studies, researchers combined MR with Blockchain. For example, the authors of [166] introduced a novel approach combining MR with blockchain-based trusted storage to enhance security and traceability in MR processes. The proposed architecture shows promise in protecting reasoning data and processes, and its extension to network management could involve integrating the trusted reasoning module to ensure secure and verifiable decision-making across distributed network nodes. Moreover, researchers in [171] combined MR through CBR with the security and transparency of Blockchain technology. They employ CBR to store and retrieve solutions from past cases, facilitating problem-solving. To ensure the secure sharing of this knowledge among related companies, the authors integrate Blockchain, which enables tamper-proof and transparent data sharing, enhancing the reliability and traceability of the reasoning process. Furthermore, researchers in [172] also integrated Blockchain and CBR for remanufacturing process planning in the context of circular economy development. By leveraging the Blockchain network to securely record and share remanufacturing knowledge across enterprises and employing CBR to retrieve optimal solutions based on the analysis of similarity between past and new cases, this hybrid method addresses the challenge of knowledge sharing in remanufacturing enterprises. This could be adapted for network management by using Blockchain for secure storage and sharing of historical network performance data and employing CBR to identify optimal solutions for network configuration, troubleshooting, and resource allocation, ultimately enhancing decision-making and efficiency in managing modern networks. Nonetheless, there is a scarcity of research exploring the fusion of MR and Blockchain technology. As a result, there emerges a necessity to delve into fortifying advanced MR and Blockchain methodologies within the realm of network management frameworks [168].

E. Reasoning with LLMs

In recent advancements within NLP, LLMs like ChatGPT have demonstrated significant progress [173, 174]. They excel at a wide range of application domains, including text generation, sentiment analysis, machine translation, question answering, chatbot development, and information retrieval [175]. Moreover, when LLMs reach a certain size, they demonstrate emergent behaviors, including the capacity for "reasoning" [176]. For instance, when these models are given Chain of Thoughts (CoT), they can respond to questions by laying out explicit reasoning steps [177]. This phenomenon has generated significant enthusiasm within the research community, as the capability to reason is a distinctive trait of human intelligence often perceived as lacking in existing AI systems. In this context, researchers in [30] introduced a captivating study that presented a taxonomy of reasoning techniques in LLMs. They categorized these techniques into three groups: Fully Supervised Fine-tuning, Prompting & In-Context Learning, and Hybrid Methods. Fully supervised fine-tuning in LLMs involves refining the model's performance by training it on specialized datasets that contain explicit reasoning tasks, as demonstrated [178]. However, one limitation is the necessity for datasets containing explicit reasoning, which can be difficult and time-consuming to produce. Prompting & In-Context Learning, as exemplified by techniques like CoT prompting in [177], holds the potential to employ "reasoning," whether implicit or explicit, to solve problems when given a question alongside corresponding (input, output) instances. Nevertheless, these models exhibit constraints in tackling tasks that require multi-step reasoning, potentially due to inadequate exploration of their comprehensive capabilities, as noted in [179]. Hybrid approaches integrate both training and prompting strategies. For example, in [180], Flan models were created by fine-tuning PaLM [174] and T5 [181] using 1.8k fine-tuning tasks, which encompassed CoT data. The study found that CoT data play a crucial role in maintaining reasoning capabilities.

The research community can make use of LLMs in the FCAPS framework to improve network management. For instance, addressing network anomalies in mobile networks, complicated by the vast number of network entities and potential issues, demands significant expertise and resources. LLMs offer a solution, leveraging historical troubleshooting tickets or log files to enhance the efficiency of cellular operators in diagnosing and resolving anomalies [182]. However, telecommunication management often requires real-time data analysis and decision-making, which current LLMs may not be able to support. This delay in identifying and addressing network issues can be costly. Therefore, enhancing LLMs with rapid decision-making capabilities is crucial for their adoption in telecommunication management. Additionally, implementing LLMs requires significant computational resources. This can be a barrier for small or resource-constrained organizations. Therefore, frugal LLMs that require fewer resources must be developed. Finally, integrating LLMs into existing telecommunication management systems can be challenging. Compatibility issues and the need for extensive modifications to current systems may arise. Therefore, enhancing telecommunication domain architectures is imperative to address these challenges [183]. Despite these challenges, LLMs present exciting possibilities given their emergence in the AI landscape. They can be combined with other MR approaches to improve logical problem-solving in the context of FCAPS [184].

VI. Conclusion

This paper has provided a comprehensive overview of how Machine Reasoning approaches can be used for network management within the Fault, Configuration, Accounting, Performance, Security Management framework. We began by providing an overview of the FCAPS levels. Next, we defined MR concepts and provided a taxonomy of MR approaches. We then presented various approaches that leverage MR across all levels of the FCAPS framework. Finally, we outlined future trends and open issues in MR for FCAPS-based network management. This survey provides a concise understanding of MR's role in FCAPS network management and encourages further exploration in this promising research area.

Acknowledgment

This work is supported by the European Union's Horizon Program under the 6G-Bricks project (Grant No. 101096954).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Pankaj Goyal, Rao Mikkilineni, and Murthy Ganti. "FCAPS in the business services fabric model". In: *2009 18th IEEE international workshops on enabling technologies: infrastructures for collaborative enterprises*. IEEE. 2009, pp. 45–51.

[2] Alex Gorod et al. "System of systems management: A network management approach". In: *2007 IEEE international conference on system of systems engineering*. IEEE. 2007, pp. 1–5.

[3] Zhi-Hua Zhou. *Machine learning*. Springer Nature, 2021.

[4] Nan Duan, Duyu Tang, and Ming Zhou. "Machine reasoning: Technology, dilemma and future". In: *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Tutorial Abstracts*. 2020, pp. 1–6.

[5] Christo Kurisummoottil Thomas et al. "Causal reasoning: Charting a revolutionary course for next-generation ai-native wireless networks". In: *IEEE Vehicular Technology Magazine* (2024).

[6] Mohamed Elkourdi, Asim Mazin, and Richard D Gitlin. "Towards low latency in 5G HetNets: A Bayesian cell selection/user association approach". In: *2018 IEEE 5G World Forum (5GWF)*. IEEE. 2018, pp. 268–272.

[7] Wei He et al. "Fault prediction method for wireless sensor network based on evidential reasoning and belief-rule-base". In: *IEEE Access* 7 (2019), pp. 78930–78941.

[8] Ying Yang et al. "An evidential reasoning-based decision support system for handling customer complaints in mobile telecommunications". In: *Knowledge-Based Systems* 162 (2018), pp. 202–210.

[9] XiaoMing Zhu, HongWu Ye, and SongJie Gong. "A personalized recommendation system combining case-based reasoning and user-based collaborative filtering". In: *2009 chinese control and decision conference*. IEEE. 2009, pp. 4026–4028.

[10] Ying Wang et al. "Anonymous jamming detection in 5g with bayesian network model based inference analysis". In: *2022 IEEE 23rd International Conference on High Performance Switching and Routing (HPSR)*. IEEE. 2022, pp. 151–156.

[11] Dandan Yan, Xu Yang, and Laurie Cuthbert. "Resource Allocation for Network Slicing in RAN Using Case-Based Reasoning". In: *Applied Sciences* 13.1 (2022), p. 448.

[12] Paulo César Fonseca and Edjard Souza Mota. "A survey on fault management in software-defined networks". In: *IEEE Communications Surveys & Tutorials* 19.4 (2017), pp. 2284–2321.

[13] David Mulvey et al. "Cell fault management using machine learning techniques". In: *IEEE Access* 7 (2019), pp. 124514–124539.

[14] Mourad Nouioua et al. "A survey of machine learning for network fault management". In: *Machine Learning and Data Mining for Emerging Trend in Cyber Dynamics: Theories and Applications* (2021), pp. 1–27.

[15] Sihem Cherrared et al. "A survey of fault management in network virtualization environments: Challenges and solutions". In: *IEEE Transactions on Network and Service Management* 16.4 (2019), pp. 1537–1551.

[16] Jovani Dalzochio et al. "Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges". In: *Computers in Industry* 123 (2020), p. 103298.

[17] Chengbo Qiu et al. "AI-Empowered Network Root Cause Analysis for 6G". In: *IEEE Network* (2023).

[18] Veddad Zahiragic. "A Survey of the State of the Art in the Application of Reasoning Techniques for Network Configuration Management". In: (2006).

[19] Abdelkader Mekrache et al. "Deep reinforcement learning techniques for vehicular networks: Recent advances and future trends towards 6G". In: *Vehicular Communications* 33 (2022), p. 100398.

[20] Tanmoy Chowdhury et al. "Knowledge-enhanced Neural Machine Reasoning: A Review". In: *arXiv preprint arXiv:2302.02093* (2023).

[21] Zonghan Wu et al. "A comprehensive survey on graph neural networks". In: *IEEE transactions on neural networks and learning systems* 32.1 (2020), pp. 4–24.

[22] Siddhant Arora. "A survey on graph neural networks for knowledge graph completion". In: *arXiv preprint arXiv:2007.12374* (2020).

[23] Xiang Wang, Xiangnan He, and Tat-Seng Chua. "Learning and reasoning on graph for recommendation". In: *Proceedings of the 13th international conference on web search and data mining*. 2020, pp. 890–893.

[24] Xiaojun Chen, Shengbin Jia, and Yang Xiang. "A review: Knowledge reasoning over knowledge graph". In: *Expert Systems with Applications* 141 (2020), p. 112948.

[25] Artur d'Avila Garcez et al. "Neural-symbolic learning and reasoning: A survey and interpretation". In: *Neuro-Symbolic Artificial Intelligence: The State of the Art* 342.1 (2022), p. 327.

[26] A Garcez et al. "Neural-symbolic computing: An effective methodology for principled integration of machine learning and reasoning". In: *Journal of Applied Logics* 6.4 (2019), pp. 611–632.

[27] Branko Ristic et al. "A tutorial on uncertainty modeling for machine reasoning". In: *Information Fusion* 55 (2020), pp. 30–44.

[28] Maarten Sap et al. "Commonsense reasoning for natural language processing". In: *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Tutorial Abstracts*. 2020, pp. 27–33.

[29] Shuofei Qiao et al. "Reasoning with Language Model Prompting: A Survey". In: *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2023, pp. 5368–5393.

[30] Jie Huang and Kevin Chen-Chuan Chang. "Towards Reasoning in Large Language Models: A Survey". In: *61st Annual Meeting of the Association for Computational Linguistics, ACL 2023*. Association for Computational Linguistics (ACL). 2023, pp. 1049–1065.

[31] Github. *LLM Reasoning Papers*. URL: https://github.com/atfortes/LLM-Reasoning-Papers.

[32] Kristijonas Cyras et al. "Machine reasoning explainability". In: *arXiv preprint arXiv:2009.00418* (2020).

[33] N Greenfield. "FCAPS Management for the Smart Grid High-level Summary". In: *AIS Engineering, Ed., ed* (2009).

[34] Mingxin Li et al. "Research and application of AI in 5G network operation and maintenance". In: *2020 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*. IEEE. 2020, pp. 1420–1425.

[35] Léon Bottou. "From machine learning to machine reasoning: An essay". In: *Machine learning* 94 (2014), pp. 133–149.

[36] Soham Banerjee, Pradeep Kumar Singh, and Jaya Bajpai. "A comparative study on decision-making capability between human and artificial intelligence". In: *Nature Inspired Computing: Proceedings of CSI 2015*. Springer. 2018, pp. 203–210.

[37] Frederick Hayes-Roth. "Rule-based systems". In: *Communications of the ACM* 28.9 (1985), pp. 921–932.

[38] Robert Kowalski and Keith L Clark. "Logic programming". In: *Encyclopedia of Computer Science*. 2003, pp. 1017–1031.

[39] Donald A Waterman. *A guide to expert systems*. Addison-Wesley Longman Publishing Co., Inc., 1985.

[40] Janet Kolodner. *Case-based reasoning*. Morgan Kaufmann, 2014.

[41] Lotfi A Zadeh. "Fuzzy logic". In: *Computer* 21.4 (1988), pp. 83–93.

[42] Marcin Synak, Maciej Dabrowski, and Sebastian Ryszard Kruk. "Semantic web and ontologies". In: *Semantic digital libraries*. Springer, 2009, pp. 41–54.

[43] Juan F Sequeda, Marcelo Arenas, and Daniel P Miranker. "On directly mapping relational databases to RDF and OWL". In: *Proceedings of the 21st international conference on World Wide Web*. 2012, pp. 649–658.

[44] Judea Pearl. "Bayesian networks". In: (2011).

[45] Matthew Richardson and Pedro Domingos. "Markov logic networks". In: *Machine learning* 62 (2006), pp. 107–136.

[46] Frédérick Garcia and Emmanuel Rachelson. "Markov decision processes". In: *Markov Decision Processes in Artificial Intelligence* (2013), pp. 1–38.

[47] Sean R Eddy. "Hidden markov models". In: *Current opinion in structural biology* 6.3 (1996), pp. 361–365.

[48] Christopher JCH Watkins and Peter Dayan. "Q-learning". In: *Machine learning* 8 (1992), pp. 279–292.

[49] John Schulman et al. "Proximal policy optimization algorithms". In: *arXiv preprint arXiv:1707.06347* (2017).

[50] John Schulman et al. "Trust region policy optimization". In: *International conference on machine learning*. PMLR. 2015, pp. 1889–1897.

[51] Ivo Grondman et al. "A survey of actor-critic reinforcement learning: Standard and natural policy gradients". In: *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42.6 (2012), pp. 1291–1307.

[52] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT Press, 2016.

[53] Ashish Vaswani et al. "Attention is all you need". In: *Advances in neural information processing systems* 30 (2017).

[54] Chadi Helwe, Chloé Clavel, and Fabian Suchanek. "Reasoning with transformer-based models: Deep learning, but shallow reasoning". In: *International Conference on Automated Knowledge Base Construction (AKBC)*. 2021.

[55] Santoshi Kumari and TP Pushphavati. "Question Answering and Text Generation Using BERT and GPT-2 Model". In: *Computational Methods and Data Engineering: Proceedings of ICCMDE 2021*. Springer, 2022, pp. 93–110.

[56] Pengpeng Shao et al. "Tucker decomposition-based temporal knowledge graph completion". In: *Knowledge-Based Systems* 238 (2022), p. 107841.

[57] Sitao Luan et al. "When Do We Need GNN for Node Classification?" In: *arXiv preprint arXiv:2210.16979* (2022).

[58] Chen Gao et al. "Graph neural networks for recommender system". In: *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*. 2022, pp. 1623–1625.

[59] Jing Zhang et al. "Neural, symbolic and neural-symbolic reasoning on knowledge graphs". In: *AI Open* 2 (2021), pp. 14–35.

[60] Matt Gardner et al. "Neural semantic parsing". In: *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics: Tutorial Abstracts*. 2018, pp. 17–18.

[61] Homa Fashandi. "Neural Module Networks: A Review". In: *Neurocomputing* (2023), p. 126518.

[62] Prithviraj Sen et al. "Neuro-symbolic inductive logic programming with logical neural networks". In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 36. 8. 2022, pp. 8212–8219.

[63] Paulo Vitor de Campos Souza. "Fuzzy neural networks and neuro-fuzzy networks: A review the main techniques and applications used in the literature". In: *Applied soft computing* 92 (2020), p. 106275.

[64] Henry Kautz. "The third ai summer: Aaai robert s. engelmore memorial lecture". In: *AI Magazine* 43.1 (2022), pp. 105–125.

[65] Yarin Gal and Zoubin Ghahramani. "Dropout as a bayesian approximation: Representing model uncertainty in deep learning". In: *international conference on machine learning*. PMLR. 2016, pp. 1050–1059.

[66] Siqi Nie, Meng Zheng, and Qiang Ji. "The deep regression bayesian network and its applications: Probabilistic deep learning for computer vision". In: *IEEE Signal Processing Magazine* 35.1 (2018), pp. 101–111.

[67] Giuseppe Marra and Ondřej Kuželka. "Neural markov logic networks". In: *Uncertainty in Artificial Intelligence*. PMLR. 2021, pp. 908–917.

[68] Volodymyr Mnih et al. "Human-level control through deep reinforcement learning". In: *Nature* 518.7540 (2015), pp. 529–533.

[69] Kai Arulkumaran et al. "Deep reinforcement learning: A brief survey". In: *IEEE Signal Processing Magazine* 34.6 (2017), pp. 26–38.

[70] Volodymyr Mnih et al. "Playing atari with deep reinforcement learning". In: *arXiv preprint arXiv:1312.5602* (2013).

[71] Ziyu Wang et al. "Dueling network architectures for deep reinforcement learning". In: *International conference on machine learning*. PMLR. 2016, pp. 1995–2003.

[72] Timothy P Lillicrap et al. "Continuous control with deep reinforcement learning". In: *arXiv preprint arXiv:1509.02971* (2015).

[73] Tuomas Haarnoja et al. "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor". In: *International conference on machine learning*. PMLR. 2018, pp. 1861–1870.

[74] Scott Fujimoto, Herke Hoof, and David Meger. "Addressing function approximation error in actor-critic methods". In: *International conference on machine learning*. PMLR. 2018, pp. 1587–1596.

[75] Volodymyr Mnih et al. "Asynchronous methods for deep reinforcement learning". In: *International conference on machine learning*. PMLR. 2016, pp. 1928–1937.

[76] Github. *Neural Symbolic and Probabilistic Logic Papers*. URL: https://github.com/thuwzy/Neural-Symbolic-and-Probabilistic-Logic-Papers.

[77] Arun Das and Paul Rad. "Opportunities and challenges in explainable artificial intelligence (xai): A survey". In: *arXiv preprint arXiv:2006.11371* (2020).

[78] Freddy Lecue. "On the role of knowledge graphs in explainable AI". In: *Semantic Web* 11.1 (2020), pp. 41–51.

[79] Janne Ali-Tolppa et al. "Self-healing and resilience in future 5G cognitive autonomous networks". In: *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*. IEEE. 2018, pp. 1–8.

[80] Ana Gómez-Andrades et al. "Methodology for the design and evaluation of self-healing LTE networks". In: *IEEE Transactions on Vehicular Technology* 65.8 (2015), pp. 6468–6486.

[81] Javier Cózar, José M Puerta, and José A Gámez. "An application of dynamic Bayesian networks to condition monitoring and fault prediction in a sensored system: A case study". In: *International Journal of Computational Intelligence Systems* 10.1 (2017), pp. 176–195.

[82] Haibin Zhang et al. "Fault detection and repairing for intelligent connected vehicles based on dynamic Bayesian network model". In: *IEEE Internet of Things Journal* 5.4 (2018), pp. 2431–2440.

[83] Multazamah Alias, Navrati Saxena, and Abhishek Roy. "Efficient cell outage detection in 5G HetNets using hidden Markov model". In: *IEEE Communications Letters* 20.3 (2016), pp. 562–565.

[84] Jiajin He and Hui Zhao. "Fault diagnosis and location based on graph neural network in telecom networks". In: *2020 International Conference on Networking and Network Applications (NaNA)*. IEEE. 2020, pp. 304–309.

[85] Zhuotong Li et al. "Demonstration of fault localization in optical networks based on knowledge graph and graph neural network". In: *2020 Optical Fiber Communications Conference and Exhibition (OFC)*. IEEE. 2020, pp. 1–3.

[86] Zhuotong Li et al. "Fault localization based on knowledge graph in software-defined optical networks". In: *Journal of Lightwave Technology* 39.13 (2021), pp. 4236–4246.

[87] Ping Liu et al. "Unsupervised detection of microservice trace anomalies through service-level deep bayesian networks". In: *2020 IEEE 31st International Symposium on Software Reliability Engineering (ISSRE)*. IEEE. 2020, pp. 48–58.

[88] Jianpeng Li, Kun Zhu, and Yang Zhang. "Knowledge-Assisted Few-Shot Fault Diagnosis in Cellular Networks". In: *2022 IEEE Globecom Workshops (GC Wkshps)*. IEEE. 2022, pp. 1292–1297.

[89] Yukyung Lee, Jina Kim, and Pilsung Kang. "Lanobert: System log anomaly detection based on bert masked language model". In: *Applied Soft Computing* (2023), p. 110689.

[90] Chris Egersdoerfer, Di Zhang, and Dong Dai. "Early Exploration of Using ChatGPT for Log-based Anomaly Detection on Parallel File Systems Logs". In: (2023).

[91] Chaoli Zhang et al. "Netrca: an effective network fault cause localization algorithm". In: *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE. 2022, pp. 9316–9320.

[92] Álvaro Carrera, Eduardo Alonso, and Carlos A Iglesias. "A Bayesian argumentation framework for distributed fault diagnosis in telecommunication networks". In: *Sensors* 19.15 (2019), p. 3408.

[93] Kai Yang et al. "Deep network analyzer (DNA): A big data analytics platform for cellular networks". In: *IEEE Internet of Things Journal* 4.6 (2016), pp. 2019–2027.

[94] Harrison Mfula and Jukka K Nurminen. "Adaptive root cause analysis for self-healing in 5G networks". In: *2017 International Conference

on High Performance Computing & Simulation (HPCS). IEEE. 2017, pp. 136–143.

[95] Rongyu Liang, Feng Liu, and Jie Liu. “A belief network reasoning framework for fault localization in communication networks”. In: *Sensors* 20.23 (2020), p. 6950.

[96] Chia-Cheng Yen et al. “Graph neural network based root cause analysis using multivariate time-series kpis for wireless networks”. In: *NOMS 2022-2022 IEEE/IFIP Network Operations and Management Symposium*. IEEE. 2022, pp. 1–7.

[97] Wenhao Jiang and Yuebin Bai. “APGNN: Alarm Propagation Graph Neural Network for fault detection and alarm root cause analysis”. In: *Computer Networks* 220 (2023), p. 109485.

[98] Ha Manh Tran and Jürgen Schönwälder. “DisCaRia—distributed case-based reasoning system for fault management”. In: *IEEE Transactions on Network and Service Management* 12.4 (2015), pp. 540–553.

[99] Arsalan Saeed, Osianoh Glenn Aliu, and Muhammad Ali Imran. “Controlling self healing cellular networks using fuzzy logic”. In: *2012 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE. 2012, pp. 3080–3084.

[100] Jessica Moysen and Lorenza Giupponi. “A reinforcement learning based solution for self-healing in LTE networks”. In: *2014 IEEE 80th Vehicular Technology Conference (VTC2014-Fall)*. IEEE. 2014, pp. 1–6.

[101] Cheng Chen et al. “A cell outage compensation mechanism based on IPSO for 5G ultra-dense small cell networks”. In: *2021 IEEE 26th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*. IEEE. 2021, pp. 1–6.

[102] Amirhossein Shaghaghi et al. “Proactive and AoI-aware failure recovery for stateful NFV-enabled zero-touch 6G networks: Model-free DRL approach”. In: *IEEE Transactions on Network and Service Management* 19.1 (2021), pp. 437–451.

[103] Vilho Räisänen, Nokia Bell, and Kasper Apajalahti. “Reasoning in agent-based network management”. In: *NOMS 2018-2018 IEEE/IFIP Network Operations and Management Symposium*. IEEE. 2018, pp. 1–7.

[104] Iván Díaz et al. “Ontological configuration management for wireless mesh routers”. In: *IP Operations and Management: 9th IEEE International Workshop, IPOM 2009, Venice, Italy, October 29-30, 2009. Proceedings 9*. Springer. 2009, pp. 116–129.

[105] Alex Randles et al. “Ontology Driven Closed Control Loop Automation”. In: *2023 IEEE 9th International Conference on Network Softwarization (NetSoft)*. IEEE. 2023, pp. 528–533.

[106] Morteza Hashemi Farzaneh and Alois Knoll. “An ontology-based plug-and-play approach for in-vehicle time-sensitive networking (TSN)”. In: *2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. IEEE. 2016, pp. 1–8.

[107] Francisco Luque-Schempp, Laura Panizo, Pedro Merino, et al. “AutomAdapt: Zero Touch Configuration of 5G QoS Flows extended for Time-Sensitive Networking”. In: *IEEE Access* (2023).

[108] Erisa Karafili et al. “Towards a framework for automatic firewalls configuration via argumentation reasoning”. In: *NOMS 2020-2020 IEEE/IFIP network operations and management symposium*. IEEE. 2020, pp. 1–4.

[109] Huangxun Chen et al. “Software-defined network assimilation: bridging the last mile towards centralized network configuration management with NAssim”. In: *Proceedings of the ACM SIGCOMM 2022 Conference*. 2022, pp. 281–297.

[110] Kasper Apajalahti et al. “StaRe: Statistical reasoning tool for 5G network management”. In: *The Semantic Web: ESWC 2016 Satellite Events, Heraklion, Crete, Greece, May 29–June 2, 2016, Revised Selected Papers 13*. Springer. 2016, pp. 21–25.

[111] Kasper Apajalahti et al. “Combining ontological modelling and probabilistic reasoning for network management”. In: *Journal of Ambient Intelligence and Smart Environments* 9.1 (2017), pp. 63–76.

[112] Amanpreet Kaur and Harsh Sadawarti. “Dynamic Resource Allocation Using a DRL Method in 5G Network”. In: *International Journal of Intelligent Systems and Applications in Engineering* 11.5s (2023), pp. 501–509.

[113] Adithya Hegde, Sameer G Kulkarni, and Abhinandan S Prasad. “COUNSEL: Cloud Resource Configuration Management using Deep Reinforcement Learning”. In: *2023 IEEE/ACM 23rd International Symposium on Cluster, Cloud and Internet Computing (CCGrid)*. IEEE. 2023, pp. 286–298.

[114] Miloud Bagaa, Karim Boutiba, and Adlen Ksentini. “On using Deep Reinforcement Learning to dynamically derive 5G New Radio TDD pattern”. In: *2021 IEEE Global Communications Conference (GLOBECOM)*. IEEE. 2021, pp. 1–6.

[115] Buseung Cho, Kuinam J Kim, and Jin-Wook Chung. “CBR-based network performance management with multi-agent approach”. In: *Cluster Computing* 20 (2017), pp. 757–767.

[116] Angelos-Christos Maroudis et al. “Leveraging graph neural networks for SLA violation prediction in cloud computing”. In: *IEEE Transactions on Network and Service Management* (2023).

[117] Zhaolong Ning et al. “Joint computing and caching in 5G-envisioned Internet of vehicles: A deep reinforcement learning-based traffic control system”. In: *IEEE Transactions on Intelligent Transportation Systems* 22.8 (2020), pp. 5201–5212.

[118] Ahmed Al-Saadi, Rossitza Setchi, and Yulia Hicks. “Semantic reasoning in cognitive networks for heterogeneous wireless mesh systems”. In: *IEEE Transactions on Cognitive Communications and Networking* 3.3 (2017), pp. 374–389.

[119] Eliseu M Oliveira, Rafael Freitas Reale, and Joberto SB Martins. “Cognitive Management of Bandwidth Allocation Models with Case-Based Reasoning-Evidences Towards Dynamic BAM Reconfiguration”. In: *2018 IEEE Symposium on Computers and Communications (ISCC)*. IEEE. 2018, pp. 00397–00403.

[120] Qingmin Meng et al. “Bayesian Network Prediction of Mobile User Throughput in 5G Wireless Networks”. In: *2018 10th International Conference on Communications, Circuits and Systems (ICCCAS)*. IEEE. 2018, pp. 291–295.

[121] Md Shirajum Munir et al. “Neuro-symbolic Explainable Artificial Intelligence Twin for Zero-touch IoE in Wireless Network”. In: *arXiv preprint arXiv:2210.06649* (2022).

[122] Nasir Khan et al. “Explainable and Robust Artificial Intelligence for Trustworthy Resource Management in 6G Networks”. In: *IEEE Communications Magazine* (2023).

[123] Shashank Jere et al. “Machine Learning-assisted Bayesian Inference for Jamming Detection in 5G NR”. In: *arXiv preprint arXiv:2304.13660* (2023).

[124] Chang Choi and Junho Choi. “Ontology-based security context reasoning for power IoT-cloud security service”. In: *IEEE Access* 7 (2019), pp. 110510–110517.

[125] Bibu Gao and Wenqiang Zhang. “A method of combining hidden Markov model and convolutional neural network for the 5G RCS message filtering”. In: *Applied Sciences* 11.14 (2021), p. 6350.

[126] Reeta Devi et al. “Implementation of intrusion detection system using adaptive neuro-fuzzy inference system for 5G wireless communication network”. In: *AEU-International Journal of Electronics and Communications* 74 (2017), pp. 94–106.

[127] Tianyue Liu et al. “Nt-gnn: Network traffic graph for 5g mobile iot android malware detection”. In: *Electronics* 12.4 (2023), p. 789.

[128] Mohamed Amine Ferrag et al. “SecureFalcon: The Next Cyber Reasoning System for Cyber Security”. In: *arXiv preprint arXiv:2307.06616* (2023).

[129] Bhagvan Kommadi. “Cognition as a service-5G based CaaS”. In: *2020 IEEE-HYDCON*. IEEE. 2020, pp. 1–5.

[130] Jorge Maestre Vidal and Marco Antonio Sotelo Monge. “Framework for anticipatory self-protective 5G environments”. In: *Proceedings of the 14th International Conference on Availability, Reliability and Security*. 2019, pp. 1–9.

[131] KC Lalropuia and Vandana Gupta. “A Bayesian game model and network availability model for small cells under denial of service (DoS) attack in 5G wireless communication network”. In: *Wireless Networks* 26 (2020), pp. 557–572.

[132] Ying He et al. “Secure social networks in 5G systems with mobile edge computing, caching, and device-to-device communications”. In: *IEEE Wireless Communications* 25.3 (2018), pp. 103–109.

[133] Stan Wong. “The fifth generation (5G) trust model”. In: *2019 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE. 2019, pp. 1–5.

[134] Ruihong Zhang and Zhihua Hu. “Access control method of network security authentication information based on fuzzy reasoning algorithm”. In: *Measurement* 185 (2021), p. 110103.

[135] Jing Zhang et al. “Edge computing-based privacy-preserving authentication framework and protocol for 5G-enabled vehicular networks”. In: *IEEE Transactions on Vehicular Technology* 69.7 (2020), pp. 7940–7954.

[136] Luis Suárez et al. “Formalization of a security access control model for the 5G system”. In: *2020 11th International Conference on Network of the Future (NoF)*. IEEE. 2020, pp. 150–158.

[137] German Peinado Gomez et al. "Security policies definition and enforcement utilizing policy control function framework in 5G". In: *Computer Communications* 172 (2021), pp. 226–237.

[138] Zhihong Tian et al. "Automated attack and defense framework for 5G security on physical and logical layers". In: *arXiv preprint arXiv:1902.04009* (2019).

[139] Yanbin Sun et al. "Automated attack and defense framework toward 5G security". In: *IEEE Network* 34.5 (2020), pp. 247–253.

[140] Chengzhi Jiang et al. "An adaptive information security system for 5G-enabled smart grid based on artificial neural network and case-based learning algorithms". In: *Frontiers in Computational Neuroscience* 16 (2022), p. 872978.

[141] Estefania Coronado et al. "Zero touch management: A survey of network automation solutions for 5G and 6G networks". In: *IEEE Communications Surveys & Tutorials* (2022).

[142] Madhusanka Liyanage et al. "A survey on Zero touch network and Service Management (ZSM) for 5G and beyond networks". In: *Journal of Network and Computer Applications* 203 (2022), p. 103362.

[143] Hatim Chergui et al. "Toward zero-touch management and orchestration of massive deployment of network slices in 6G". In: *IEEE Wireless Communications* 29.1 (2022), pp. 86–93.

[144] Sabra Ben Saad, Bouziane Brik, and Adlen Ksentini. "A Trust and Explainable Federated Deep Learning Framework in Zero Touch B5G Networks". In: *GLOBECOM 2022-2022 IEEE Global Communications Conference*. IEEE. 2022, pp. 1037–1042.

[145] Hatim Chergui et al. "Zero-touch ai-driven distributed management for energy-efficient 6g massive network slicing". In: *Ieee Network* 35.6 (2021), pp. 43–49.

[146] Abdelkader Mekrache, Karim Boutiba, and Adlen Ksentini. "Combining Network Data Analytics Function and Machine Learning for abnormal traffic detection in Beyond 5G". In: *2023 IEEE Global Communications Conference (GLOBECOM)*. IEEE. 2023, pp. 1–6.

[147] Ovidiu Iacoboaiea et al. "From Design to Deployment of Zero Touch Deep Reinforcement Learning WLANs". In: *IEEE Communications Magazine* 61.2 (2022), pp. 104–109.

[148] Mohamed Mekki et al. "XAI-Enabled Fine Granular Vertical Resources Autoscaler". In: *2023 IEEE 9th International Conference on Network Softwarization (NetSoft)*. IEEE. 2023, pp. 161–169.

[149] Vasileios Theodorou et al. "Blockchain-based zero touch service assurance in cross-domain network slicing". In: *2021 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*. IEEE. 2021, pp. 395–400.

[150] Pradeep Kathail. "Machine Reasoning–Improving AIOps for Intent Based Networks". In: ().

[151] Engin Zeydan and Yekta Turk. "Recent advances in intent-based networking: A survey". In: *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*. IEEE. 2020, pp. 1–5.

[152] Aris Leivadeas and Matthias Falkner. "A survey on intent based networking". In: *IEEE Communications Surveys & Tutorials* (2022).

[153] Jacopo Massa et al. "Declarative Provisioning of Virtual Network Function Chains in Intent-based Networks". In: *2023 IEEE 9th International Conference on Network Softwarization (NetSoft)*. IEEE. 2023, pp. 522–527.

[154] Talha Ahmed Khan et al. "GAN and DRL based intent translation and deep fake configuration generation for optimization". In: *2020 International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE. 2020, pp. 347–352.

[155] Jieyu Lin et al. "AppleSeed: Intent-Based Multi-Domain Infrastructure Management via Few-Shot Learning". In: *2023 IEEE 9th International Conference on Network Softwarization (NetSoft)*. IEEE. 2023, pp. 539–544.

[156] Sana Shams, Bareera Sadia, and Muhammad Aslam. "Intent Detection in Urdu Queries Using Fine-Tuned BERT Models". In: *2022 16th International Conference on Open Source Systems and Technologies (ICOSST)*. IEEE. 2022, pp. 1–6.

[157] Xiaoang Zheng, Aris Leivadeas, and Matthias Falkner. "Intent Based Networking management with conflict detection and policy resolution in an enterprise network". In: *Computer Networks* 219 (2022), p. 109457.

[158] Yogesh Sharma et al. "SLA Management in Intent-Driven Service Management Systems: A Taxonomy and Future Directions". In: *ACM Computing Surveys* (2023).

[159] Yogesh Sharma et al. "Intent Negotiation Framework for Intent-Driven Service Management". In: *IEEE Communications Magazine* 61.6 (2023), pp. 73–79.

[160] Antonio Marsico et al. "An automated negotiation framework for application-aware transport network services". In: *Optical Switching and Networking* 38 (2020), p. 100571.

[161] John A Barnden. "Combining uncertain belief reasoning and uncertain metaphor-based reasoning". In: *Proceedings of the Twentieth Annual Conference of the Cognitive Science Society*. Routledge. 2022, pp. 114–119.

[162] Khoi D Hoang et al. "New distributed constraint reasoning algorithms for load balancing in edge computing". In: *PRIMA 2019: Principles and Practice of Multi-Agent Systems: 22nd International Conference, Turin, Italy, October 28–31, 2019, Proceedings 22*. Springer. 2019, pp. 69–86.

[163] Matthew Mantle, Sotirios Batsakis, and Grigoris Antoniou. "Large scale distributed spatio-temporal reasoning using real-world knowledge graphs". In: *Knowledge-Based Systems* 163 (2019), pp. 214–226.

[164] Helio Monte-Alto, Mariela Morveli-Espinoza, and Cesar Tacla. "Argumentation-Based Multi-Agent Distributed Reasoning in Dynamic and Open Environments". In: (2023).

[165] Ramin Firouzi, Rahim Rahmani, and Theo Kanter. "Federated learning for distributed reasoning on edge computing". In: *Procedia Computer Science* 184 (2021), pp. 419–427.

[166] Yichuan Wang et al. "Trusted Storage Architecture for Machine Reasoning based on Blockchain". In: *IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. IEEE. 2022, pp. 1–6.

[167] Chafika Benzaıd, Tarik Taleb, and Muhammad Zubair Farooqi. "Trust in 5G and beyond networks". In: *IEEE Network* 35.3 (2021), pp. 212–222.

[168] Khaled Salah et al. "Blockchain for AI: Review and open research challenges". In: *IEEE Access* 7 (2019), pp. 10127–10149.

[169] Ruijiao Tian et al. "Blockchain for ai: A disruptive integration". In: *2022 IEEE 25th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*. IEEE. 2022, pp. 938–943.

[170] Abir El Azzaoui et al. "Block5GIntell: Blockchain for AI-enabled 5G networks". In: *IEEE Access* 8 (2020), pp. 145918–145935.

[171] Imane ETTAHIRI and Karim DOUMI. "Dynamic Enterprise Architecture planning using case-based reasoning and blockchain". In: *Procedia Computer Science* 204 (2022), pp. 714–721.

[172] Shengqiang Li et al. "A hybrid method of blockchain and case-based reasoning for remanufacturing process planning". In: *Journal of Intelligent Manufacturing* 32 (2021), pp. 1389–1399.

[173] OpenAI ChatGPT. *optimizing language models for dialogue. OpenAI. 2022*. 2023.

[174] Aakanksha Chowdhery et al. "Palm: Scaling language modeling with pathways". In: *Journal of Machine Learning Research* 24.240 (2023), pp. 1–113.

[175] Jean Kaddour et al. "Challenges and Applications of Large Language Models". In: *arXiv preprint arXiv:2307.10169* (2023).

[176] Jason Wei et al. "Emergent abilities of large language models". In: *arXiv preprint arXiv:2206.07682* (2022).

[177] Takeshi Kojima et al. "Large language models are zero-shot reasoners". In: *Advances in neural information processing systems* 35 (2022), pp. 22199–22213.

[178] Dan Hendrycks et al. "Measuring mathematical problem solving with the math dataset". In: *arXiv preprint arXiv:2103.03874* (2021).

[179] Karthik Valmeekam et al. "Large Language Models Still Can't Plan (A Benchmark for LLMs on Planning and Reasoning about Change)". In: *arXiv preprint arXiv:2206.10498* (2022).

[180] Hyung Won Chung et al. "Scaling instruction-finetuned language models". In: *arXiv preprint arXiv:2210.11416* (2022).

[181] Colin Raffel et al. "Exploring the limits of transfer learning with a unified text-to-text transformer". In: *The Journal of Machine Learning Research* 21.1 (2020), pp. 5485–5551.

[182] Ali Maatouk et al. "Large Language Models for Telecom: Forthcoming Impact on the Industry". In: *arXiv preprint arXiv:2308.06013* (2023).

[183] Lina Bariah et al. "Large Language Models for Telecom: The Next Big Thing?" In: *arXiv preprint arXiv:2306.10249* (2023).

[184] Liangming Pan et al. "Logic-lm: Empowering large language models with symbolic solvers for faithful logical reasoning". In: *arXiv preprint arXiv:2305.12295* (2023).

Abdelkader Mekrache (Member, IEEE) is a PhD condidate at EURECOM's Communication Systems Department. His primary focus is advanced Network Management frameworks in next-generation wireless networks under the supervision of Prof. Adlen Ksentini. He is an active participant in collaborative research, and notably contributes to the OpenAirInterface (OAI) project. His research interests include Next-Generation Networking, 5G Core Network, Network Management & Orchestration, Artificial Intelligence, and Reasoning Algorithms for 5G networks and beyond.

Adlen Ksentini (Senior Member, IEEE) is a professor in the Communication Systems Department of EURECOM. He is leading the Network softwarization group activities related to Network softwarization, 5G/6G, and Edge Computing. Adlen Ksentini's research interests are Network Sofwerization and Network Cloudification, focusing on topics related to network virtualization, Software Defined Networking (SDN), and Edge Computing for 5G and 6G networks. He has been participating to several H2020 and Horizon Europe projects on 5G and beyond, such as 5G!Pagoda, 5GTransformer, 5G!Drones, MonB5G, ImagineB5G, 6GBricks, 6G-Intense, Sunrise-6G and AC3. He is the technical manager of 6G-Intense and AC3, on zero-touch management of 6G resources and applications, and Cloud Edge Continuum, respectively. He is interested in the system and architectural issues but also in algorithm problems related to those topics, using Markov Chains, Optimization algorithms, and Machine Learning (ML). Adlen Ksentini has given several tutorials in IEEE international conferences, IEEE Globecom 2015, IEEE CCNC 2017/2018/2023, IEEE ICC 2017, IEEE/IFIP IM 2017, IEEE School 2019. Adlen Ksentini is a member of the OAI board of directors, where he is in charge of OAI 5G Core Network and O-RAN management (O1, E2) for OAI RAN activities.

Christos Verikoukis (Senior Member, IEEE) received the Ph.D. degree from Technical University of Catalonia (UPC), Barcelona, Spain, in 2000. He is currently an Associate Proferssor with the Univerisity of Patras and an Collaborating Faculty member with the ISI/ATH. He has authored 158 journal papers and over 200 conference papers. He is also a co-author of three books, 14 chapters in other books, and two patents. He has participated in more than 40 competitive projects, and has served as a project coordinator of several funded projects from the European Comission and of national projects in Greece and Spain. He is currently the IEEE ComSoc GITC vice-chair and the editor-in-chief of the IEEE Networking Letters.