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Machine learning-based zero-touch network and service management: a survey

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ABSTRACT

The exponential growth of mobile applications and services during the last years has challenged the existing network infrastructures. Consequently, the arrival of multiple management solutions to cope with this explosion along the end-to-end network chain has increased the complexity in the coordinated orchestration of different segments composing the whole infrastructure. The Zero-touch Network and Service Management (ZSM) concept has recently emerged to automatically orchestrate and manage network resources while assuring the Quality of Experience (QoE) demanded by users. Machine Learning (ML) is one of the key enabling technologies that many ZSM frameworks are adopting to bring intelligent decision making to the network management system. This paper presents a comprehensive survey of the state-of-the-art application of ML-based techniques to improve ZSM performance. To this end, the main related standardization activities and the aligned international projects and research efforts are deeply examined. From this dissection, the skyrocketing growth of the ZSM paradigm can be observed. Concretely, different standardization bodies have already designed reference architectures to set the foundations of novel automatic network management functions and resource orchestration. Aligned with these advances, diverse ML techniques are being currently exploited to build further ZSM developments in different aspects, including multi-tenancy management, traffic monitoring, and architecture coordination, among others. However, different challenges, such as the complexity, scalability, and security of ML mechanisms, are also identified, and future research guidelines are provided to accomplish a firm development of the ZSM ecosystem.

1. Introduction

Next-Generation Networks (NGNs) are expected to cope with a wide and flexible range of services, technologies, verticals, and devices. This heterogeneity leads to a clear increase in the complexity of the activities related to network infrastructure management [1]. The paradigms of Software-Defined Networking (SDN) and Network Function Virtualization (NFV) have emerged as convenient solutions to adaptively handle the dynamic demand of network resources. Nevertheless, the network softwarization clearly calls for innovative solutions to tackle the issues related to the automatic and efficient management of resources and the adequate provision of end-to-end Quality of Experience (QoE) to end-users. Both aspects are of prominent importance because the virtualized resources are mapped to physical entities that may belong to diverse providers.

To enable an automatically orchestrated management of network resources across different domains and to warrant the end-user's QoE, a broad spectrum of both Zero-touch Network and Service Management (ZSM) and Network Slicing (NS) techniques is currently being developed [2–4]. While the latter permits the creation of a chain of network functions that logically conform to a dedicated virtual network that fulfills certain user requirements, vertical industry, or service, the former provides methods to achieve these goals in an unsupervised manner. Thus, over a common physical infrastructure, multiple logical networks can operate independently, abandoning the traditional approach of static, fixed, and human-managed physical networks. Network slices must operate elastically by efficiently handling the transported traffic flows together with the service-level requirements of clients. Therefore, communication among different service or infrastructure providers is crucial. Having a zero-touch slice orchestrator with a holistic view of the end-to-end path is also of paramount importance for the efficient management of resources. Consequently, this orchestrator should handle information regarding the network resource status in different involved domains (i.e., Radio Access Network (RAN), Multi-access Edge

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Computing (MEC) segment, transport network, and core architecture) to intelligently adapt the operation to the variations in the requirements of different services over time. Fig. 1 depicts a general end-to-end slicing architecture.

Network management decisions must be made by considering different (sometimes contradicting) objectives because each type of service presents diverse requirements (e.g., maximising data rate, minimising energy consumption, or reducing end-to-end latency). In addition, the inherent heterogeneity of NGNs makes it difficult to cope with the fluctuations of virtualized topologies or unstable conditions of wireless channels. Thus, the integration of intelligent functions within the network architecture is a must. Such integration is useful for (i) flexibly reacting to changes in network conditions, (ii) monitoring the traffic status, (iii) controlling the network resources, and most importantly, (iv) forecasting the system behavior as a whole and taking actions in advance. This is particularly important in guaranteeing scalability and providing the required QoE to end-users.

To this end, Machine Learning (ML) has recently emerged as a highly promising alternative to cope with the aforementioned challenges in terms of processing information, generating meaningful knowledge, and providing intelligent decision-making capabilities to NGN management systems following a ZSM-based approach [5–7]. ML is a field of study that enables computers to learn without being explicitly programmed. For this to be done, ML-based techniques receive a dataset that is processed by one or multiple learning algorithms to build useful models. ML algorithms are usually categorized into four different families [8]: Supervised Learning (SL), Unsupervised Learning (UL), Semi-Supervised Learning (SSL), and Reinforcement Learning (RL).

The application of different ML techniques enriches the network infrastructure with Intelligent and Autonomous Network Functions (IANFs) in its different domains (Fig. 1). The type of technique to use depends on the nature of the information gathered and the aimed objectives. However, regardless of the particular techniques employed, this strategy drastically changes how current network management systems operate. Using ML provides the architecture with flexibility and automatic management capabilities that have never been seen before. However, several challenges must still be overcome, considering that ML-powered techniques for enabling ZSM frameworks are still in their infancy [9].

To the best of our knowledge, no prior extensive and up-to-date surveys have specifically covered the topic of ML-fueled ZSM. Some works have explored the application of ML in network slicing [10], SDN and NFV [11], resource management [12], and wireless and mobile networks [13–15]. In Ref. [10], the authors reviewed the application of ML to manage the network slice operation in the Fifth-Generation (5G) mobile network. Meanwhile, [11] examined how ML can be used to address the challenges that SDN and NFV present, specifically remarking the issues caused by having limited access to available network resources. Ref. [12] analyzed Deep Reinforcement Learning (DRL)-based resource management schemes for 5G heterogeneous networks, which is a complex problem caused by the interference between small and macro cells. Ref. [13] provided a comprehensive survey on the application of ML techniques to the Internet of Things (IoT) wireless communications. Using a bottom-up approach, the authors examined the existing work at the physical, data-link, and network layers. Ref. [14] addressed the deployment of Deep Learning (DL) techniques in mobile and wireless networking, covering diverse tasks, such as mobile data analysis, user localization, network control, network security, and wireless signal processing. In a similar manner [15], reviewed multiple DRL proposals applied to well-known communications and networking issues, such as data rate control, data offloading, network security, and dynamic network access. Nevertheless, these studies offered a partial view of the problem because they addressed only certain network segments or were limited to specific AI models. Therefore, they did not address all the needed operations to achieve a totally automated and self-managed network infrastructure following the ZSM paradigm.

Given the relevance and the novelty of ZSM, this paper discusses the necessity of integrating intelligence within NGN infrastructures to effectively handle the heterogeneity of devices, services, and technologies that will coexist in future hyper-connected ecosystems. We provide an overview of the ML techniques suitable for adoption in network management, as well as current NS and ZSM standards, architectures, and models. We also aim to recapitulate the different proposals from the research community to manage and orchestrate NGN functions by using ML. Thus, we identify the different network control functions required in ZSM-managed architectures and provide insights regarding the most proper ML techniques for implementing them. With this dissection, we analyze specific ZSM frameworks developed under the umbrella of international projects and standardization and research efforts. We also highlight the different areas that need further study to reach an adequate level of maturity.

The remainder of this paper is organized as follows. Section 2 provides an overview of the ML techniques used in network management; Section 3 describes the standardization activities and architectures proposed in different research projects; Section 4 presents in detail several approaches of NGN infrastructure management and orchestration using ML; Section 5 discusses the research challenges in this field and the future lines of work; Section 6 concludes the survey. Table 1 lists all the acronyms used in this paper.

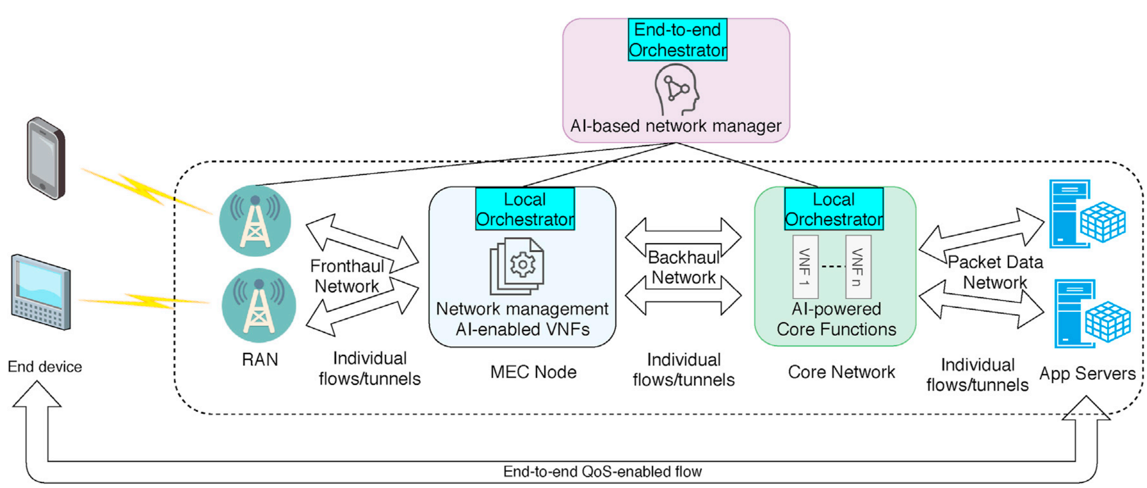

Fig. 1. Overall Zero-touch Network and Service Management (ZSM) vision.

Table 1
Definition of acronyms in alphabetical order.

Acronym	Meaning
3GPP	3rd-Generation Partnership Project
5G	5th-Generation mobile network
AI	Artificial Intelligence
BS	Base Station
CNN	Convolutional Neural Network
DE	Decision-making Element
DL	Deep Learning
DLT	Distributed Ledger Technologies
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DT	Decision Tree
E2E	End to End
ECMP	Equal-Cost Multi-Path
EM	Expectation-Maximization
ETSI	European Telecommunications Standards Institute
eNB	evolved NodeB
FNN	Feedforward Neural Network
GAN	Generative Adversarial Network
GANA	Generic Autonomic Networking Architecture
GBT	Gradient Boosted Tree
IANF	Intelligent and Autonomous Network Functions
IEC	International Electrotechnical Commission
IoT	Internet of Things
ISO	International Organization for Standardization
ITU	International Telecommunication Union
JTC	Joint Technical Committee
k-NN	k-Nearest Neighbor
KP	Knowledge Plane
LDA	Linear Discriminant Analysis
LoRa	Long Range
LSTM	Long Short-Term Memory
LTE	Long-term Evolution
MANO	Management and Orchestration
MDP	Markov Decision Process
MEC	Multi-access Edge Computing
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MNO	Mobile Network Operator
MVNO	Mobile Virtual Network Operator
NB	Naive Bayes
NFV	Network Function Virtualization
NGN	Next Generation Network
NN	Neural Network
NS	Network Slicing
OAI	Open Air Interface
OSPF	Open Shortest Path First
QDA	Quadratic Discriminant Analysis
QoE	Quality of Experience
QoS	Quality of Service
QoT	Quality of Transmission
RAN	Radio Access Network
RAT	Radio Access Technology
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SC	Standardization Subcommittee
SDN	Software Defined Networking
SL	Supervised Learning
SLA	Service Level Agreement
SINR	Signal to Interference plus Noise Ratio
SON	Self-organizing Network
SSL	Semi-supervised Learning
SVM	Support Vector Machine
TC	Technical Committee
UE	User Equipment
UL	Unsupervised Learning
VM	Virtual Machine
VoIP	Voice over IP
WG	Working Group
ZSM	Zero-touch Network and Service Management

2. ML techniques for zero-touch NGN management

This section presents a brief overview of the ML techniques adopted to automate network and service management. We briefly describe these methods for each of the four families introduced in the previous section.

2.1. Supervised learning

SL techniques receive a dataset with vectors of input features and the expected output for each sample and learn a model from such data. The function can generate continuous values (regression) or a class label that identifies the given input (classification). Thus, while regression algorithms are asked to predict a numerical value from the input, classification algorithms permit the specification of the class of input among a given set. Supervised learning techniques are usually employed to identify classes of traffic by automatically inspecting the packets, allowing the classification of service requirements, or enabling the usage of that information to forecast different trends in user behavior. The following are some supervised learning techniques that can be applied to ZSM:

- Linear/polynomial regression computes a linear/polynomial combination of the features of the input samples to learn a model. Depending on the dimensionality of the feature vector, it generates a regression line or a hyperplane that can be used to predict the value of future instances. The application of regression-based ZSM mechanisms assists operators in QoS-based network planning [11].
- Decision Tree (DT) is a graph employed to classify unlabeled input, whose characteristics are learned from labeled samples in the training stage. A specific feature is examined in each binary branching node. By comparing its value with a certain threshold, the algorithm follows the right or the left branch. The leaves represent final nodes with the class to which the input belongs. The planning and design of networks are eased with DTs because they can be applied to forecast user behavior based on past traffic profiles [10].
- Random Forest (RF) is a model that uses several DTs, where each of them provides as output individual class (classification) or mean (regression) predictions. The RF algorithm combines the result of each one to produce the final output. The idea is that a combination of multiple learning models improves the overall result. The errors made by each tree must have a low correlation with each other to produce accurate predictions. In a similar way to DTs, RF models can predict the requirements of mobile network subscribers by analyzing traffic records [11].
- Logistic regression is a binary classification learning algorithm based on the concept of probability, where the hypothesis limits the cost function between 0 and 1. The classifier returns a probability score between these two values when the input is processed. Depending on the selected threshold, it decides if the example belongs to one class or the other. This kind of regression algorithms can be efficiently applied to channel allocation problems [16] or classification of operation data [10].
- k-Nearest Neighbor (k-NN) assigns classes based on the proximity of the data points among them based on some distance function (e.g., Euclidean). For each input sample, the algorithm evaluates the nearest training samples and chooses the most common class to assign it to the unlabeled input. In this way, the application of this technique to traffic classification is straightforward [11].
- Support Vector Machine (SVM) aims to find a hyperplane that best divides the data points belonging to different classes and acts as a decision boundary in an n-dimensional space, n being the number of features. The support vectors are the closest points to the hyperplane, and they define its position and orientation, allowing the model to find nonlinear boundaries among classes. This enables efficient spectrum management and prediction in the RAN [13].
- Naive Bayes (NB) is a probability classifier, which is mainly used to classify user traffic and model attacker behavior [11]. It uses the Bayes theorem, assuming that the input features are independent of each other, and no correlation exists among them.

- Neural Network (NN) is a model based on the concatenation of artificial neurons, called perceptrons, which take several inputs with an associated weight and produce a single output. These individual units are combined in consecutive layers of different sizes to produce complex decision making. The power and the versatility of NNs make them useful and applicable to a wide variety of network functions, including traffic classification and prediction, RAN management, multi-domain orchestration, and resource management [11,13,16].

2.2. Unsupervised learning

UL algorithms do not receive any labeled example or desired output from the dataset. On the contrary, these schemes must seek the input structure. They promote understanding of the analyzed data and identify patterns, but do not predict the output value or class for specific input. UL mechanisms are useful for grouping traffic flows with similar characteristics and assigning them to common slices to provide different levels of Quality of Service (QoS) depending on the available network resources. Some of the most extended techniques are as follows:

- Clustering determines the internal grouping of a set of unlabeled data, organizes similar examples together, and distinguishes them from other groups. This model is commonly used to group and classify user traffic, devices, and log data [10,11,16]. It is also a good choice to deal with interference management in the RAN [17,18]. Specific clustering algorithms are k-means, k-medoid, and Expectation-Maximization (EM), among many others.
- Neural Network (NN): Aside from their extensive use in SL, NNs are also exploited with non-labeled datasets. Thus, the output layer learns how to organize the input data and find patterns without needing a specific target. From the UL perspective, NNs can be applied to traffic and data classification problems [11,13].
- Dimensionality reduction helps represent the input data with fewer dimensions to reduce redundant information that complicates the discovery of intrinsic patterns, which is very suitable for traffic data analysis and classification [13].

2.3. Semi-supervised learning

SSL algorithms receive as input a small amount of unlabeled data together with a large amount of labeled data. The objective of this type of technique is the same as that of SL, but they use many unlabeled examples to improve the accuracy of the produced model. Furthermore, SSL algorithms are less time consuming and tedious compared to SL. SSL techniques show their effectiveness in network traffic classification, where the initial amount of labeled examples is low. SSL may refer to two types of learning [19]:

- Transductive learning aims to infer the correct labels for the provided unlabeled data. Self-training is the most common transductive method for SSL. In this technique, a classifier is trained with the labeled data, which is later used to classify the unlabeled set. Then, the unlabeled data and its prediction that ensure correct prediction are attached to the training set. With these new data, the classifier is retrained, and the process is repeated.
- Inductive learning algorithms use the labeled and unlabeled sets as the training examples, with the aim to predict unseen data.

We have not found specific references or examples about the direct application of SSL to network automation, but these ML models can be useful for both SL and UL use cases because they share characteristics with them [13,16].

2.4. Reinforcement Learning

RL algorithms teach processing units how to make decisions by trial and error to maximize the reward they obtain in each task. The idea behind RL is that the rewarded behavior will be repeated in the future. RL algorithms are employed in a wide variety of use cases, such as slice admission strategies, data migration in the MEC, Radio Access Technology (RAT) selection, and allocation of resources for NS. The RL algorithms are classified into two main types as follows:

- Model-based algorithms use a model of the environment that they can access or learn themselves. By using the model, they can plan in advance the actions that provide the best outcome. For instance, they can evaluate the consequences of deciding on one or another option in advance, enabling usage in proactive resource allocation in mobile networks [16].
- Model-free agents have to learn a model from experience. This can result in bias because the agent may perform well in the learned model but not in the real environment. An example of a model-free algorithm is Q-learning, which can be applied to track the variations in user behavior and traffic flows to select the most appropriate policies [13].

3. Machine Learning in NGN management: standards, architectures, and models

This section provides a comprehensive overview of the current activities and initiatives performed toward the development of standardized ML-based ZSM mechanisms and architectures in the context of NGNs. We also review the international projects pushing for the application of ML techniques to resource provisioning, network slicing, and infrastructure management.

3.1. Standards

Different standardization bodies have devoted resources and efforts during the last years to align criteria and work toward the common goal of a global ML-driven ZSM framework, which will act as the foundation pillar for the design and development of new AI-based network management and orchestration mechanisms. These initiatives are led by important bodies and organizations, such as ETSI, ITU-T, and 3GPP. The subsequent section provides an overview of these standardization activities.

3.1.1. ETSI Zero-touch network & Service Management (ZSM)

ETSI created this working group [20] in 2017 to accelerate the definition of an end-to-end architectural framework designed for closed-loop automation and optimized for data-driven ML and Artificial Intelligence (AI) algorithms. This group was one of the first initiatives to boost the development of automatic network management schemes and the one that coined the ZSM term. At the moment, the ISG ZSM group has already published reports on the ZSM requirements [21], terminology [22], and reference architecture [23]. The group is currently working on the specification of management interfaces for the orchestration and automation of end-to-end NS, cross-domain services, closed-loop operations, and security aspects of the ZSM framework.

The ZSM framework reference architecture follows the trend of evolving rigid management systems toward more flexible services. As shown in Fig. 2, the architecture defines a set of building blocks that enable the construction of more complex service and function chains using interoperation patterns. It is composed of distributed management and data services organized in management domains and integrated via an integration fabric used to enable service consumption, communication, and integration with third-party systems. Supported by the cross-domain integration fabric, every management domain provides a set of ZSM service capabilities through functions that expose or consume a set of service end-points.

Domain intelligence services [23] are in charge of intelligent closed-loop automation by supporting different degrees of automated

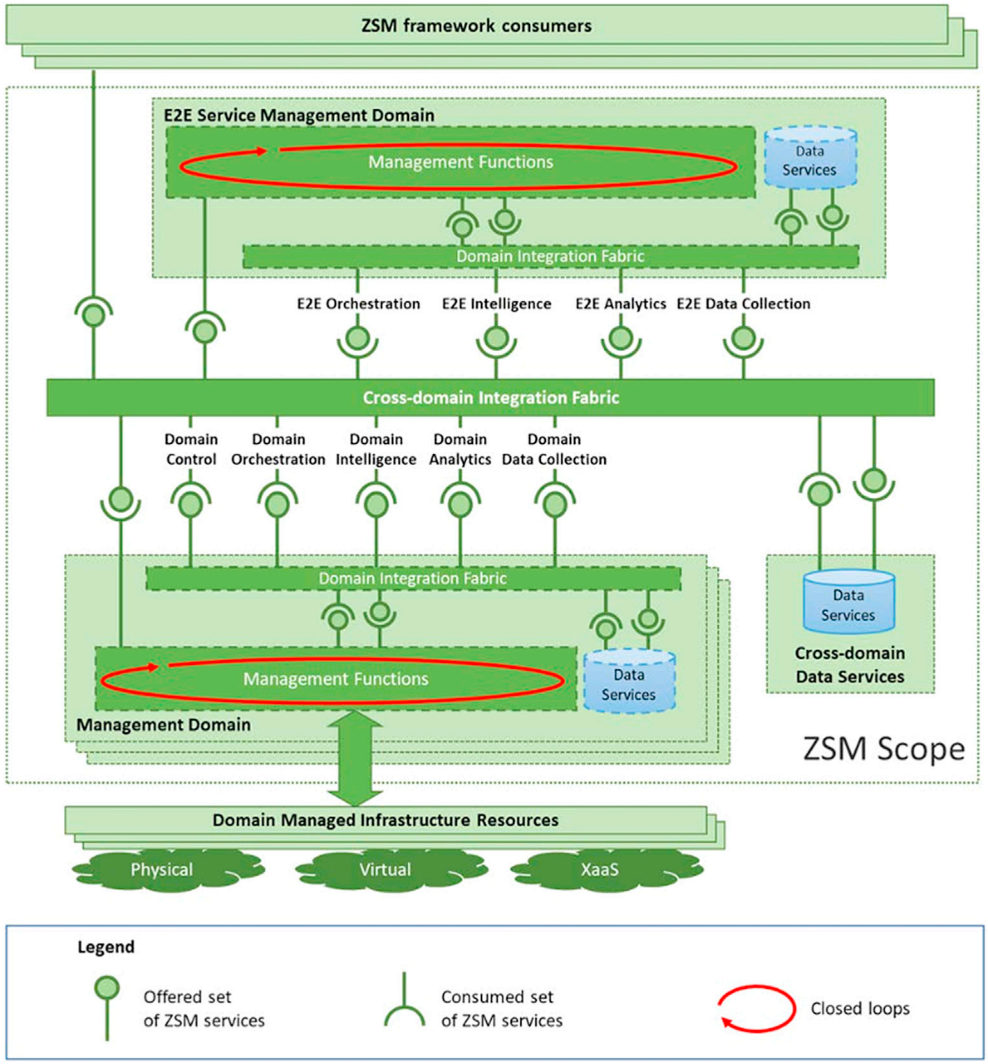

Fig. 2. ETSI ZSM reference architecture. Extracted from [23].

decision making. These services can be categorized into three classes: decision support, decision making, and action planning. Decision making is enabled by using decision support services, such as those based on AI and ML. The used information is provided by the ZSM services defined in the data collection and analytics domains. Finally, the resulting action planning defines the orchestration actions to be executed by the ZSM services in the control and orchestration domains.

3.1.2. *ETSI Industry Specification Group (ISG) in Experiential Networked Intelligence (ENI)*

This group [24] was created to develop specifications for the definition of a cognitive network management system. The focus is oriented toward improving the operator experience to recognize and incorporate new knowledge. The selected approach enables the system to tune the offered services based on changes in environmental conditions, business goals, or user needs. Technically, the aim is to improve intelligence and efficiency in SDN, NFV, and network slicing by using AI techniques and context-aware policies. Multiple specifications have already been defined and published, covering the terminology [25], requirements [26], system architecture [27], and proof of concept framework [28]. A document covering the application of AI to networks has also been elaborated [29]. Fig. 3 presents a simplified view of the main processing components of the high-level functional architecture of ENI when an API broker is used. The architecture is founded on three main blocks that perform input processing, analysis, and output processing. The broker aims to serve as a gateway between different systems because there currently is no functional block to translate external data formats to the ENI system.

The ENI system applies policy-driven closed control loops to manage and monitor operator networks. It dynamically updates the acquired knowledge to gain an understanding of the needs of the end-users and the goals of the operators. To do this, it uses emerging technologies, such as big data analysis and AI, learning from actions automatically taken as well as those from other machines and humans. Multiple categories for the level of application of AI techniques to network management have been defined in Ref. [29], starting at basic limited aspects to fully AI-based network management. This division in categories may be useful for inexperienced users because it can guide them in choosing a specific implementation of an AI-assisted network, providing information about the self-configuration and adaptation capabilities for each kind of use case.

3.1.3. *ETSI Technical Committee (TC) in the core network and interoperability (INT)*

The ETSI TC INT [30] aims to develop specifications applied to 3GPP networks to test interoperability, conformance, performance, and security. The group produces test descriptions and cases to enable testing within the 5G network slice service assurance space along with SDN, NFV, and E2E orchestration. As a part of this committee, the Autonomic

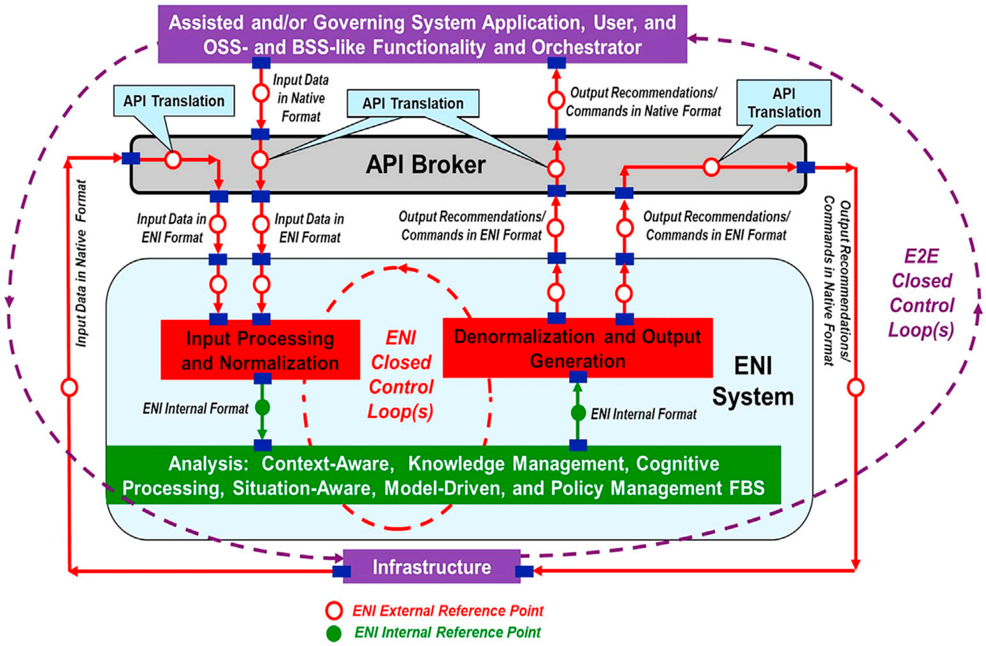

Fig. 3. ETSI ISG ENI high-level functional architecture. Extracted from [27].

Management and Control Intelligence for Self-managed Fixed & Mobile Integrated Networks Working Group (AFI WG) published in 2018 a new standard [31], in which the architectural components for autonomic, cognitive, and self-managed networking are provided. The defined ETSI Generic Autonomic Networking Architecture (GANA) model establishes a paradigm called autonomic management and control of networks and services based on closed-loop service instantiations and adaptive operations.

The GANA model defines a main and functional entity, namely the Decision-making Element (DE), that drives a control loop meant to configure and regulate the state and behavior of one or more Managed Entities (MEs) (i.e., system resources). Fig. 4 shows the GANA framework. The architecture is divided into abstraction levels for self-management functionality, in which internetworking control loops and their associated DEs can be designed. DEs realize the features of the autonomous system as a result of the decision-making behavior that

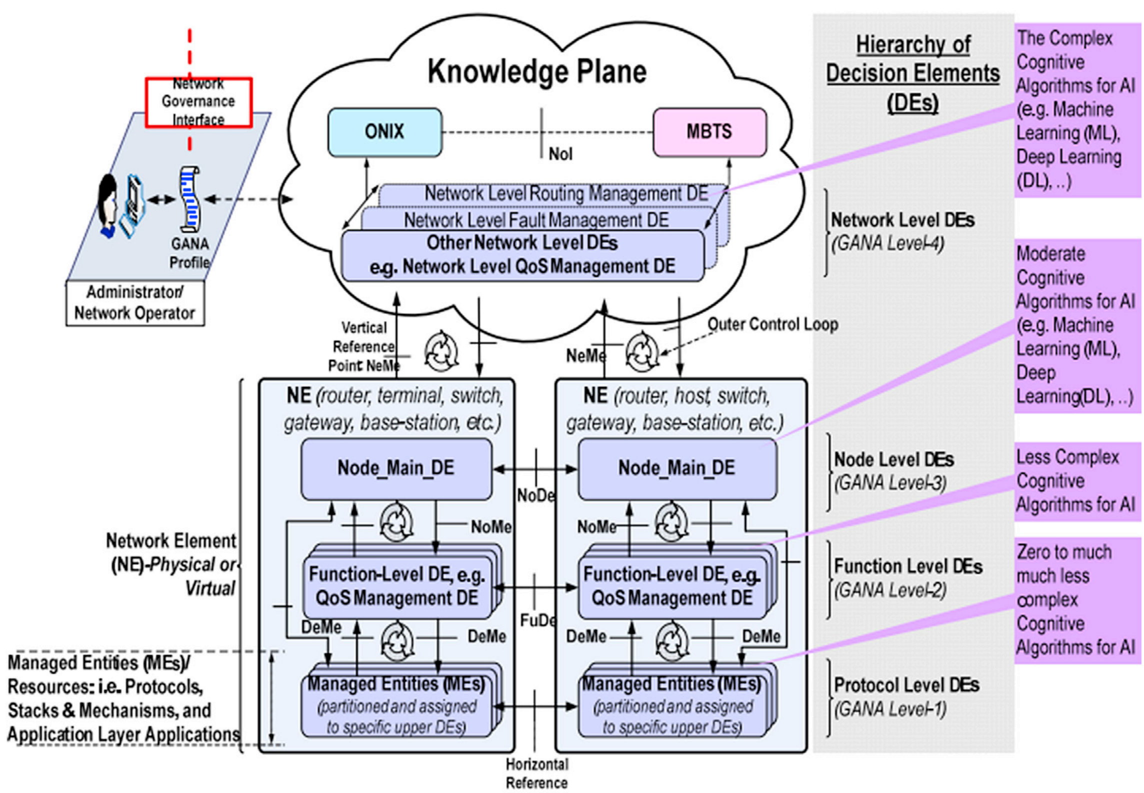

Fig. 4. ETSI GANA model. Extracted from [ETSI TS 103 195–2].

performs dynamic and adaptive management and control of its associated MEs and their configurable and controllable parameters. Such elements can be embedded in a network element or in a higher level of architecture and can be virtual or physical. The lower the position of the element in the architecture hierarchy, the less complex the cognitive algorithm that can be integrated into it The GANA Knowledge Plane (KP) is defined as a controlling system within the network that builds and maintains high-level models of the desired network behavior to provide services and advice to other network elements. It operates by enhancing and evolving the system intelligence, replacing and reloading DEs at specific abstraction levels of management and control.

The GANA reference model can also be applied in designing future network architectures that include self-managing capabilities. The model is not constrained by any implementation-oriented architecture and tries to avoid the limitations of the current technology-specific networking solutions. Thus, it defines and separates generic concepts and architectural principles for autonomic, cognitive, and self-managed networking. ETSI GANA is a relevant framework in relation to the other standardization efforts because having such a generalized structure enables the positioning of DEs at four basic abstraction levels for self-management within network nodes depending on the desired functionality. This is complemented by the ETSI ENI work on the improvement of the operator experience by adding closed-loop AI mechanisms based on context-aware and metadata-driven policies to adjust services and offer resources based on business goals.

3.1.4. ITU-T focus group on Machine Learning for future networks

This group [32] was established in 2017 with the objective of drafting technical reports and specifications for ML for NGNs, including interfaces, architectures, protocols, algorithms, and data formats. It is an open initiative in which ITU members and non-members collaborate to study ML methods for NGNs. The group has provided public documents covering topics, such as ML architectural frameworks for NGN [33] and evaluated the achieved intelligence levels [34], data handling [35], and use cases [36].

One of the main contributions of this group is the ML-based infrastructure-management pipeline [33] depicted in Fig. 5. As shown in the figure, this high-level architectural design is based on three main components. The ML pipeline is a set of logical nodes that can be combined to form an ML application in a network. The ML function orchestrator is a logical node whose main tasks are to manage and coordinate nodes in the ML pipeline. Hence, it is in charge of selecting the ML model and chaining and placing the nodes. The ML sandbox is an isolated domain that allows the hosting of independent ML pipelines to train, test, and evaluate them before their deployment in a production environment.

Furthermore, the ITU-T provides examples for the realization of a high-level functional architecture [33] and a data-handling framework [35] on an IMT-2020 network (i.e., a standalone 5G network). In this way, the functioning of both the architecture and the framework within the 5G infrastructure is described, pointing out the role of each node and its positioning.

3.1.5. 3GPP

In 2008, the 3rd-Generation Partnership Project (3GPP) introduced Release 8 [37] of its wireless broadband communication standard. This was the first one defining the Long-Term Evolution (LTE) technology that improved the spectrum efficiency, increased the downlink and uplink bandwidths, and introduced an all-IP network. The 3GPP brought forward the concept of a Self-Organizing Network (SON) considering the new requirements from the network operators in terms of infrastructure management flexibility and to reduce the operating expenditure associated with the network planning and management of a large number of nodes from more than one vendor. This paradigm has evolved in each release since its initial definition [38]; hence, it has been extended and improved until Release 16 [39].

SONs are defined as a set of use cases that cover all aspects of network operation. They are based on the paradigm that the network should be able to self manage its own resources so that it can achieve optimal quality and performance and fulfill the network operators' requirements in an automatic fashion. SON solutions can be divided into three

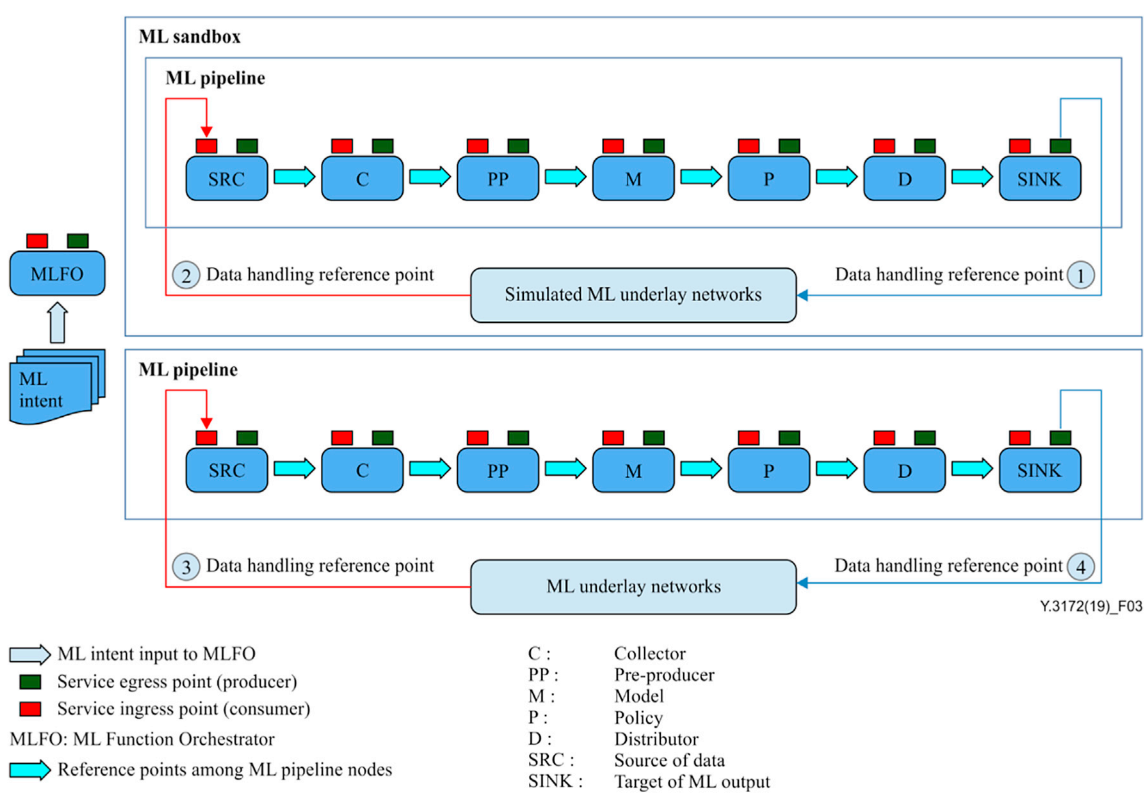

Fig. 5. ITU-T architectural framework for the integration of Machine Learning (ML) in future network components. Extracted from [33].

Table 2
Summary of the ZSM standards.

Standard	Organization	ML-based	Objective	Architecture	Use cases
ZSM	ETSI	Yes	Boost automatic network management	Integration fabric	Orchestration and automation of end-to-end NS, cross-domain services, closed-loop operations, and security aspects
ENI	ETSI	Yes	Define cognitive network management	API Broker	Policy-driven closed control loops to manage and monitor operator networks
INT	ETSI	Yes	Reference model to design self-managing network architectures	Hierarchical abstract modules	Architecture design template, closed-loop and self-organizing networks and cross-domain services
ML for future networks	ITU-T	Yes	Draft technical reports and specifications for ML in NGNs	Modular pipeline	High-level functional architecture and data handling framework in 5G networks
SON	3GPP	No	Reduce operating expenditure	3GPP architecture	Base station self-configuration, automated and continuous optimization, and automated troubleshooting and mitigation

categories: (i) self-configuration (Release 8), in which newly deployed base stations are plug-and-play configured; (ii) self-optimization (Release 9), which covers the dynamic improvement of coverage, capacity, handover procedures, and interference mitigation; and (iii) self-healing (Release 10), in which the network has capabilities to automatically detect and mitigate system failures.

Note that SON-based architectures are not powered by AI; instead, other approaches are adopted. Concretely, these architectures rely on the closed-loop paradigm to provide autonomous functionality. The standard defines three types of SON: (i) centralized, in which the optimization algorithms are executed in the management system of the operator; (ii) distributed, in which the SON mechanisms run in the network elements; and (iii) hybrid, a combination of centralized and distributed solutions. In this way, the following two roles are defined: the IRPManager, which should be able to control the automatic procedures according to the objectives and targets of the operator; and the IRPAgent, which should support the capabilities to perform the requested action and report to the IRPManager the success or failure result. A key point in this design is that an easy transition procedure must be provided to change between operator-controlled (open-loop) to autonomous (closed-loop) because the network operator gains more trust in the SON mechanisms. Regarding the SON algorithms themselves, the 3GPP decided not to standardize them [38,39].

In light of the previous dissection, ETSI ZSM, ETSI TC INT, ITU-T, and ETSI ISG ENI have been paving the way toward ML-driven ZSM by studying the specific application of AI to network management and orchestration. While the latter is more focused on ZSM applications in the industry and the improvement of operator experience, the efforts of ETSI ZSM are oriented to the development and orchestration of automatic network management functions, which is perfectly aligned with the topic explored in this survey. In a similar way, ETSI TC INT AFI WG has proposed a reference model that can be applied in the design of ZSM network architectures. Asides from that, the ITU-T group is also applying ML to infrastructure management, but without a fully automated architecture vision by now. In contrast, although 3GPP efforts do not rely on ML techniques, the standard follows the closed-loop architecture paradigm, in which the network elements are monitored, and optimization algorithms react to the events and changes in the network. Table 2 presents a summary of the discussed standards. These initiatives are in their first steps because their main contributions to this date are the definition of the reference architectures of each group. More specific contributions are expected during the next times; therefore, ZSM and AI researchers should closely follow the updates of these standardization bodies considering that the currently proposed architectures will be additionally extended and enriched with new functionalities.

3.2. Research projects

Asides from standardization initiatives, such as those dissected earlier, different international projects have also devoted great efforts to design, develop, and implement ML-based ZSM mechanisms over already deployed complex network infrastructures. Concretely, in the following, we focus on reviewing European projects that were recently finished or are ongoing.

3.2.1. CogNet

The CogNet project[1] is an H2020 5GPPP project co-funded by the European Commission under the ICT-14-2014 call. This project aimed to contribute to the field of autonomous network management through the use of ML techniques employed for gathering available network data and recognizing events and conditions to adequately respond to the dynamic changes occurring in the network. As shown in Fig. 6, the CogNet Smart Engine is the main component of the system that is in charge of receiving the records, pre-processing them, selecting the appropriate ML model, and applying the chosen module to process the data. The developed architecture can dynamically adapt to changes by combining ML models and network management policies. The NFV framework continuously forwards its state and usage records to the engine, which analyzes the data and generates some key values employed by the policy engine for policy recommendation. The policy engine can also recommend actions to the Management and Orchestration (MANO) stack, transforming the abstract actions specified in certain policies into concrete ones based on the state and configuration information from the MANO stack.

Multiple ML techniques were employed in this project to address specific 5G network challenges in four different testbeds. SVMs were used to analyze user traffic and classify it to perform network state predictions. In a similar manner, Deep NNs (DNNs) were employed in traffic analysis use cases, such as in the real-time processing of social media streams. Traffic estimation and user throughput prediction were also supported by using RF and using RAN performance and the radio statistics of the device as the input parameters. The network structure was optimized to improve massive multimedia data flow handling with a three-stage component that employed k-means classification and optimization based on linear regression and heuristics. From the implementation perspective, Python and R were the selected languages to implement the ML components using well-known libraries, such as Scikit-learn,[2] or programming some of them from scratch. On the data acquisition side, the modules were based on Apache Spark[3] with custom modifications.

Consequently, the outcome of this project can be considered from two perspectives: first, from the design and the implementation of new ML algorithms or methods, such as the fast iterative algorithm for feature selection in unsupervised learning presented in Ref. [41], or the usage of the probabilistic principal component analysis to leverage scores in

[1] https://5g-ppp.eu/cognet/.
[2] https://scikit-learn.org/.
[3] https://spark.apache.org/.

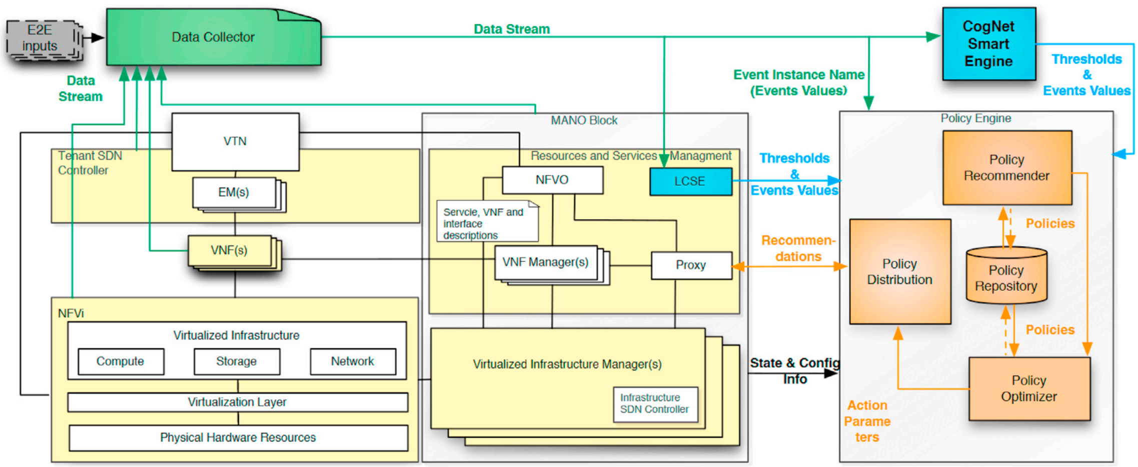

Fig. 6. Architecture of the CogNet project. Extracted from [40].

unsupervised feature selection shown in Ref. [42]; and second, from the exhaustive application of these techniques and existing ones to the overall network management process that has served to obtain highly valuable insights about their performance in different tasks. As an example, the use of deep CNNs to detect noisy neighbors in cloud infrastructures was explored in Ref. [43]. Another example is the usage of NN to enforce SLAs in networking services involving SDNs and VNFs introduced in Ref. [44].

3.2.2. *Selfnet*

Selfnet[4] is a project supported by the European Commission's Horizon 2020 Programme through the H2020-ICT-2014-2 call. It aimed to develop a self-organizing network management framework for 5G. Using a virtualized network infrastructure combined with AI, the framework automates network maintenance, deployment, monitoring, and service provisioning. The architecture [45] was based on an autonomic control loop, aggregating an analyzer, an autonomic manager, a rule-based tactical autonomic language, and an orchestrator.

Selfnet had the sub-objectives of designing, implementing, and validating a self-monitoring and detection subsystem, a distributed SON automatic management engine subsystem, and a SON orchestration and virtual infrastructure management subsystem. Considering these elements, the main contribution of the project focused on the reduction of the service creation time in virtualized 5G networks. Moreover, Selfnet was committed to creating a secure, reliable, and dependable network with virtual zero downtime. Some of the main outcomes of this project have been published. In Ref. [46], Selfnet is presented as a fully autonomic and intelligent framework based on SDNs and NFVs to reduce the operational expenditure of the 5G ecosystem. Furthermore, other works focused on more specific tasks. Ref. [47] presented a clustering-based monitoring tool for requesting statistics to measure the traffic flow in SDNs. Ref. [48] proposed an artificial immune network to project and focused on the identification of a suitable architecture that would enable the introduction of components to host advanced AI algorithms. The developed modules will support vertical-oriented monitoring, control-loop stability, orchestration, resource control, anomaly detection, forecasting, and inference powered by ML-based elements.

The project recently started to produce promising results in the networking area, as can be seen in Ref. [49], where an algorithm for providing near-optimal VNF sharing among verticals was presented. The concept of service shifting and how it can be integrated into 5G network slices was also described in Ref. [50].

3.2.3. *INSPIRE-5Gplus*

INSPIRE-5Gplus[5] is an ongoing project funded by the H2020 program (ICT-20-2019 call), which aims to improve the security in 5G and NGN architectures by leveraging existing assets and introducing novel solutions exploiting the potential of AI and blockchain. Through these objectives, INSPIRE-5Gplus will provide intelligent and trusted multi-tenancy solutions across multi-tenant infrastructures while improving security.

In the initial study of 5G security status and future trends [51], the increasing demand for advancements in the current security management solutions to cope with the new requirements demanded by technologies, such as ZSM and AI, has been highlighted. Regarding network management, the main challenge is the integration and the implementation of a security mechanism by adopting automation solutions. Although AI has been used within the broad field of security for a long time, synergies with NGNs, such as advanced 5G architectures, are still at an early stage. In security-critical applications, AI is considered a key enabler in 5G networks. Multiple approaches will be evaluated during project development, including anomaly/intrusion detection in distributed systems, classification of security incidents, and telemetry, among others.

Fig. 7 depicts the end-to-end security management architecture proposed in INSPIRE-5Gplus. The security management domain was decoupled from the other domains to reduce the system complexity. It permits the evolution of security management both independently and at the cross-domain level. Each domain also operates in an intelligent closed-loop to provide AI-driven orchestration and management. More insights about this project's approach can be found in Ref. [52]. Aside from the current initial outcomes, promising results are expected because the project partners are closely working with the ETSI ZSM standardization group.

3.2.4. *5G-VINNI*

The 5G-VINNI[6] project started in 2018 with support from the European Commission's H2020 programme under the ICT-17-2017 call. The project mainly aimed to provide an end-to-end facility that validates the performance of new 5G technologies by hosting trials of advanced services. To do this, the proposed strategy includes the building of several interworking 5G sites with user-friendly ZSM systems. However, 5G-VINNI is not intended to simply be a group of interconnected test sites; it is envisioned to enable the design and development of new flexible and dynamic network architectures and the deployment and design of new

[4] https://selfnet-5g.eu/.

[5] https://inspire-5gplus.eu/.

[6] https://5g-vinni.eu/.

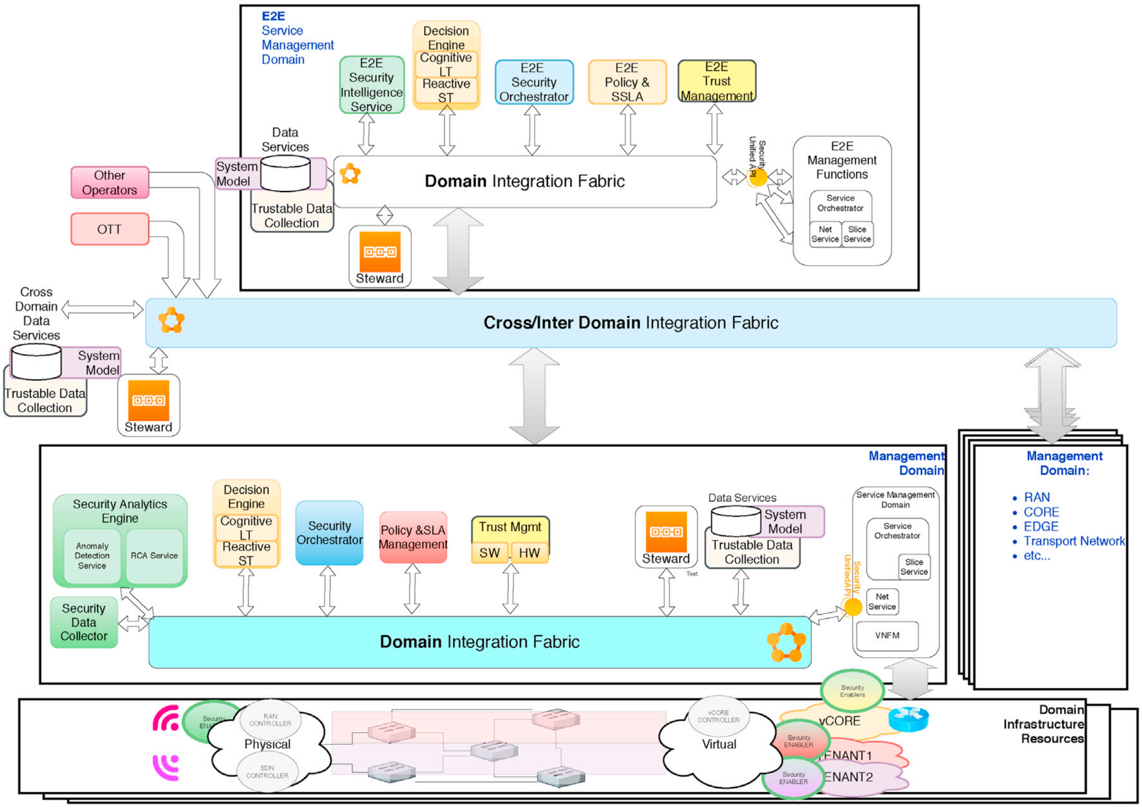

Fig. 7. Architecture of the INSPIRE-5Gplus platform. Extracted from [52].

services. This will convert interconnected sites into a cloud-based network instance with no functional boundaries that will be implemented across multiple locations. The project's main sites are located in Norway, the UK, Spain, and Greece. Its experimentation sites are in Portugal and Germany. In this way, 5G VINNI will provide a platform for testing and putting in trial multiple services by combining a comprehensive test framework, multiple interconnected 5G RAN and core infrastructures, and end-to-end ZSM. Heretofore, the main contributions of this project focus on the design and setup of the architecture and network slicing subsystems that compose both the main and experimentation sites [53–55]. In this regard, directions and guidelines for 5G service implementation and deployment are provided in different produced documents [56–58]. The project is also exploring new closed-loop management techniques like the service assurance architecture for network slices as a service presented in Ref. [59].

3.2.5. 5GZORRO

5GZORRO[7] is an ongoing project funded by the H2020 program under the ICT-20-2019 call. Its goal is to apply distributed AI techniques to produce an architecture for future 5G networks consisting of automated, flexible, and multi-stakeholder combinations and composition of resources and services in a secure and trusted manner. To support the distributed functioning in the 5G end-to-end service chain, 5GZORRO proposes the adoption of Distributed Ledger Technologies (DLTs) to provide the system with efficient security and trust. Thus, the framework can implement a 5G service layer among multiple non-trusted parties, where it is possible to monitor SLAs, share the spectrum, intelligently discover resources, and automate management, among other functions. Consequently, the cross-domain orchestration supported by the service lifecycle automation can enforce security policies in multi-tenant and stakeholder environments. The project is in its inception stage; thus, there are still no public outcomes available online. However, some initial concepts of the envisioned system were presented in Ref. [60], where the project participants proposed a zero-touch security and trust conceptual architecture for ubiquitous computing and connectivity in 5G networks.

3.2.6. Other projects

Aside from the previous projects, other initiatives focused on network slicing and automatic network management. Although they did not use AI-driven solutions for their developed network resource orchestration platforms, we also reviewed them because they conducted significant research in the field of automatic NGN management. These activities laid the foundations for the present-day projects that aim to apply ML techniques to management architectures evolved from these proposals.

5GNorma[8] was one of the 5GPPP projects funded by the Horizon 2020 framework under the call H2020-ICT-2014-2. Its principal objective was to develop a mobile network architecture capable of efficiently handling fluctuations in traffic demand caused by heterogeneous networks and services. The technical approach was based on the adaptive allocation of mobile network functions. The network was decomposed in those functions and placed in the most appropriate locations. The adopted multi-tenancy approach leveraged the adaptability and the efficiency of network functions and enabled the dynamic sharing and distribution of the network resources among different operators. The principal contribution of 5GNorma, which is the main structural element of its flexible network design, are the three options for RAN slicing [61]. These configuration profiles differ by the degree of freedom offered for customization and the required complexity for implementation. In the first RAN option, each network slice may be customized down to the physical layer; thus, the maximum degree of freedom is achieved. In the second RAN type, the user-specific functionality is shared, as well as the cell-specific information. In the last RAN, the complete RAN is shared by

7 https://5gzorro.eu/.

8 http://www.it.uc3m.es/wnl/5gnorma/.

multiple tenants. As the relevant outcomes of the project, there have been multiple contributions to major standardization bodies, namely 3GPP, ETSI, IETF, IEEE, and ITU-T [62].

The 5G!Pagoda[9] project was funded by the European Commission's H2020 program under the H2020-EUJ-2016-1 call. The main objective of the project was to develop a 5G network slicing architecture to support virtualized infrastructures composed of multi-vendor network functions. To this end, the adopted approach was based on highly programmable network control, network function flexible chaining, and centralized control state management. Following this strategy, the slice-oriented operations were logically centralized and handled by the orchestrator, whereas the sliced network management allowed the slice operator to manage his network. The reference architecture [63] of the project was based on resources separated into two main groups: virtual resources built on top of the physical resources; and hardware nodes and subsystems, which can also be programmed, but offer different services. It also allowed the creation of two different generic slice types, namely common and dedicated slices. Both can cooperate and share a similar internal structure but have different roles. The dedicated slice acted as a client of the common one. Finally, the partners identified six main exploitable assets as a result of the project developments [64], namely (i) the implementation of the 5G core network to support small messages and data plane diversity, (ii) a network slice planner, (iii) programmable RAN Open Air Interface, (iv) a deep data plane programmability system, (v) a resource pool for scalable orchestration, and (vi) content delivery networking and information-centric networking as a service.

SliceNet[10] is an ongoing project supported by the European Commission Horizon 2020 Programme under the H2020-ICT-2016-2 call, and its aim is to build a control framework to support 5G vertical services built as slices. To do this, the framework consists of managed domains using network softwarization and slicing, maximizing the potential of 5G infrastructures and their services using cognitive network management. The generic SliceNet 4G-5G virtualized infrastructure deployment consists of the following components: an RAN runtime slicing system that enables the dynamic creation of slices; a FlexRAN[11] controller for monitoring and controlling the RAN domain; LL-MEC[12] controller for leveraging the SDN programmability; a JOX[13] orchestrator that natively supports network slicing; OAI-RAN and OAI-CN[14] that provide the 5G communication system; and OpenDayLight[15] for controlling L3 routing capabilities and controlled by VELOX to install the connectivity policies required to maintain multi-domain slices. A recently released ETSI technical document, which proposes the application of ETSI TC INT GANA federated knowledge planes for E2E multi-domain management and control of slices, used components prototyped and implemented in the SliceNet project.[16]

In summary, the CogNet and Selfnet projects laid the foundations of the design and development of autonomous management and orchestration frameworks for NGNs. While Cognet provided constructive knowledge about the performance results when applying ML techniques to the network management process, Selfnet developed one of the first autonomous closed-loop frameworks that aim to provision heterogeneous networks with self-organizing capabilities. In turn, 5GNorma and 5G!Pagoda deeply studied the network slicing architectures and the adaptive allocation of VNFs to efficiently handle traffic fluctuations in NGNs. In line with this, Slicenet currently focuses on the design of a 5G cognitive control framework with cross-domain network slicing capabilities, which employs state-of-the-art function virtualization techniques. Furthermore, 5G-VINNI will provide an end-to-end 5G distributed architecture with self-configuration capabilities, which will be available to host tests of advanced 5G services. Aside from that, interested researchers and practitioners should periodically track the contributions of 5GROWTH, INSPIRE-5Gplus, and 5GZORRO projects, which are now working on the automation of end-to-end communications in industry verticals, on the introduction of AI-powered security solutions in SONs, and on the development of ML- and DLT-driven ZSM security and trust distributed architecture, respectively. Table 3 presents a summary of the reviewed project's aims and approaches.

4. ML-driven network management and orchestration functions

This section discusses in-depth the research proposals addressing the application of AI to the management and orchestration of different network functions, facilitating the full integration of ZSM in NGNs. The discussion is divided according to the role of the reviewed solutions within the network and based on the network functions that must be automated using ML as described in Ref. [10]. This survey aims to concisely examine the corpus of proposals accumulated during recent years with relation to the ZSM concept. We address different approaches and methodologies to give a holistic view of the current ZSM landscape. We have conducted an exhaustive search in large academic search engines, such as science.gov, Google Scholar, Microsoft Academic, and Semantic Scholar, and the repositories of technical publishers. Table 4 presents a summary of the proposals comprehensively reviewed hereon.

4.1. Flow inspection

This is a central task in ZSM systems that involves classifying traffic depending on their source or destination, type of transported data, priority marks, etc. It aims at giving adequate treatment in terms of routing or QoS to each traffic flow.

Ref. [65] built a network slicing architecture that uses ML to classify mobile application traffic early to apply different QoS levels. They prepared a clustering model to group and label applications with similar traffic characteristics. The input data for this model were the sizes of the first five packets of each flow and the source and destination ports. They then used K-means to determine the clusters by previously normalizing all the features in the dataset. Consequently, the model set three clusters associated with three different slices (i.e., QoS categories). Next, this output was used as the training dataset to test the classification model performance with five SL algorithms, namely NB, SVM, NN, Gradient Boosted Tree (GBT), and RF. The results showed that all the algorithms achieved a high accuracy (>96%), with GBT and RF showing the best performances by classifying traffic flows with almost 100% accuracy.

Ref. [66] proposed a payload-based traffic classification using DL models in SDNs, to provide an efficient QoS for each application. They placed the classifier modules in the control plane, allowing the classification decision to be used in the data plane. The employed dataset only contained the payload of packets because omitting the header information helped improve the model generalization performance with unseen packets. The payload was treated as image data, grouping the bits into pixels. They trained two DL models to classify the network traffic, namely a multi-layer Long Short-Term Memory (LSTM), which is a special kind of NN, and a combination of a single-layer LSTM and a CNN. In addition, they used a model tuning procedure to find the optimal hyper-parameters for each dataset. Both DL models were compared on the basis of the F1-score measure. In the conducted experiments, the multi-layer LSTM model performed better than the other one. The authors claimed that this model is a promising candidate for solving the network traffic classification problem.

Phan et al. [67] developed an RL-based control framework for traffic flow matching to improve the monitoring performance in SDN networks and proactively prevent flow-table overflow in SDN switches. First, the

[9] https://5g-pagoda.aalto.fi/.
[10] https://slicenet.eu/.
[11] https://mosaic5g.io/flexran/.
[12] https://mosaic5g.io/ll-mec/.
[13] https://mosaic5g.io/jox/.
[14] https://www.openairinterface.org/.
[15] https://www.opendaylight.org/.
[16] https://slicenet.eu/slicenet-poc-contributions/.

Table 3
Summary of projects.

Project	Status	Objective	ML techniques	Technologies	Outcome
Cognet	Ended	Network autonomous management with ML	NNs. SVMs, clustering	NFV, SDN	ML algorithms or methods, applications of ML to NGNs
Selfnet	Ended	Self-organizing network management framework for 5G	NNs, clustering	NFV, SDN	Fully autonomic and intelligent framework
5GROWTH	Ongoing	Empower industries with AI-driven 5G solution	NNs	NFV	Identification of suitable architecture to host advanced AI algorithms
INSPIRE-5Gplus	Ongoing	Improve 5G and NGN security	NNs	NFV, SDN, MEC, IoT, DLTs	End-to-end security management architecture
5G-VINNI	Ongoing	Provide end-to-end ZSM facility to validate 5G performance trials	–	–	Architecture and NS subsystems
5GZORRO	Ongoing	Apply distributed AI to produce a 5G architecture	–	DLTs	Zero-touch security conceptual architecture
5GNORMA	Ended	Develop a mobile network architecture to handle traffic fluctuations	–	NFV, SDN	RAN slicing architecture
5G!PAGODA	Ended	Design a 5G NS architecture to support multi-vendor NFs	–	NFV, SDN	5G core network, programmable RAN and data plane programmability system
SliceNet	Ongoing	Build a framework to support 5G vertical services as slices	–	NFV, SDN	RAN runtime slicing system, RAN controller and an orchestrator.

Table 4
Summary of ML-driven ZSM proposals from the academia.

Work	Network function				ML algorithm							
	Flow Inspection	Multi-domain management	RAN management	Network resource management	DT	RF	k-NN	SVM	NB	NN	Clustering (k-means/ medoids)	RL
[65]	✓				✓	✓		✓	✓	✓	✓	
[66]	✓									✓		
[67]	✓							✓				✓
[68]	✓				✓	✓	✓	✓	✓	✓		
[69]		✓								✓		✓
[70]		✓								✓		
[71]		✓								✓		
[72]		✓	✓									✓
[73]		✓								✓		✓
[74]		✓								✓		✓
[75]			✓	✓								✓
[77]			✓							✓		✓
[79]			✓							✓		
[80]			✓									✓
[81]			✓					✓				
[82]			✓	✓						✓		✓
[83]			✓									✓
[76]			✓							✓		
[78]			✓							✓		
[85]				✓								✓
[86]				✓						✓		✓
[87]				✓								✓
[88]				✓								✓
[89]			✓	✓								✓
[90]				✓						✓		✓
[91]				✓						✓		
[92]				✓							✓	
[93]	✓			✓				✓				
[94]				✓	✓							

authors proposed a traffic flow matching control mechanism that uses Q-learning to optimize the traffic granularity in the data plane, considering the devices as the environment for the RL algorithm. Next, they designed a policy creation module that was integrated into the Q-DATA framework based on the previously explained mechanism. This framework efficiently provided detailed traffic flow information using SVMs to analyze the traffic and predict the performance degradation in the SDN switches. The policy creation module determined the optimum action required to improve the traffic flow matching scheme with this information. Multiple experiments were performed in a real-world scenario and demonstrated that the new framework provides significant performance benefits compared to traditional SDN controllers.

Ref. [68] proposed a proof of concept of an ML-based approach to predict the traffic demands in optical networks composed of chained VNFs. They considered the network model as a directed graph of nodes and a set of physical links. In this approach, the traffic was represented by different demands, which were flows generated between a source and a destination node during a certain period of time. The time of the experiment was divided into time intervals. The study aimed to predict the source and destination nodes. The problem was considered as a classification task, but the number of possible classes in large networks can be notably high, making the multiclass prediction quite complex. Thus, the authors simplified the problem by transforming it into a binary classification problem. To do this, they assumed that the number of learned classifiers is equal to the number of possible demands; hence, the system predicts if each demand will occur in the next time period. They considered eight different classification algorithms, namely k-NN, NN, SVM, DT, RF, Gaussian NB, Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA). The dataset was obtained from a real network that connected 12 cities in Poland. The LDA was the best classifier in all the experiments. Furthermore, the length of the VNF chains noticeably affected the classifier performance because the longer chains generated more possible demand pairs and improved the classification quality.

One of the main problems in traffic flow classification is the availability of training data, which was solved in these works by dividing the operation of the proposed systems into two stages. In the first stage, the data are prepared by using a different technique or by treating the traffic flows in a different manner. For example, [65,67] used clustering and SVMs to obtain the training data and applied SL and Q-learning, respectively, to inspect the traffic flows. A different approach was implemented in Ref. [66]. The training and classification were performed with the same traffic data, but only the headers in the training and the payload in the classification procedure are used. A promising solution for solving the lack of training data in this kind of scenario was proposed by using Generative Adversarial Networks (GANs), which permit the production of artificial data that comply with the same statistics as a given dataset. The discussed proposals showed that SL techniques are predominant over other ML models when applied to traffic flow classification because operators and network managers have pre-conceived SLAs and policies to help classify traffic flows and service requirements. In this manner, the application of QoS actions can be performed more efficiently and predefined guidelines can be followed.

4.2. Multi-domain management

Given the rise of resource-sharing approaches among different operators (i.e., multi-tenancy) or the decentralization of network functions by splitting different infrastructure segments into separated and self-contained entities, efficient and intelligent management of these distributed network domains is crucial for the adequate operation of the end-to-end system.

Ref. [69] proposed a cognitive inter-domain networking framework with multi-agent DRL and multi-broker orchestration for multi-domain optical networks. The framework permits broker agents to infer optimal service provisioning policies from the network state information with DNN. Each broker acts as an autonomous learning agent, whose brain is the DRL module. When an inter-domain service request arrives, the broker analyzes the current network state and generates a new policy using DRL to help the service manager take a certain action. The domain manager then establishes the service and returns the feedback given along with the network state and the action taken to the learning agent. The networking framework performance was evaluated in a topology with four domains and two brokers. The results showed that the agents quickly learn optimal policies, and the brokers achieve higher rewards compared with other schemes.

Liu et al. [70] presented a hierarchical learning framework for inter-domain service provisioning in software-defined elastic optical networking. Their framework was based on a hierarchical architecture of brokers, which collaborate with the managers of each domain to efficiently provide global services. Each domain manager is responsible for managing a subset of the global networks, providing intra-domain service provisioning, monitoring, and traffic engineering. The broker plane is above the domain manager plane to handle inter-domain service requests and global optimizations. The local domain managers handle intra-domain lightpath requests, list all available paths and inquire the cognition agent to get a Quality-of-Transmission (QoT) prediction. Local managers report to the broker information on the available path segments and their QoT prediction values. The broker then uses these data to establish inter-domain service provisioning. NNs are used in the cognition agents of each domain because of their strong capability to approximate complex nonlinear functions. Each domain NN uses information provided by the optical performance monitors to obtain a list of local prediction values uploaded to the broker-level NN to calculate the inter-domain predictions. The experiments showed that the framework provides an efficient provisioning scheme, while its scalability capabilities remain to be fully assessed.

In [71], the authors designed an ML QoT estimation technique for the alien wavelength light path provisioning of inter-and intra-domain traffic. The proposed framework, where the scheme was integrated, was divided into the broker, domain manager, and the data planes. Domain managers report the QoT estimations of the virtual topologies and the monitoring information of the alien wavelength to the broker. To predict the QoT, the scheme uses NN with two hidden layers and 10 nodes in each one, which was the optimal configuration the authors found. It takes as input the power measurements of all the channels and the noise level of each link. The developed estimator was tested in an experiment and showed an average estimation error of less than 6%.

Shin et al. [72] proposed an RL-based distributed radio access scheme that enables dynamic multi-channel spectrum sharing while minimizing interference among Mobile Network Operators (MNOs). This scheme is designed for scenarios where multiple MNOs share a single cellular band. A reward function based on the Signal to Interference plus Noise Ratio (SINR) is designed for MNOs to learn sharing channels fairly. The SINR of the accessed channel is used as a reward value to perform RL and select optimal radio resources to determine the frequency channel to be used. A positive value is used if the value is above a certain threshold. The reward is negative if it is below the threshold. The authors performed simulations to validate the proposal in a simplified experimental environment comprising two MNOs with two evolved Node Bs (eNBs) each. In the simulations, the reward value was obtained by using the number of collision channels and successful access channels. The results showed that the scheme guarantees the fairness of spectrum sharing among the operators and increases the throughput.

Ref. [73] proposed a DL-based prediction scheme to manage the resource leasing and caching process. This scheme aimed to improve the profit of Mobile Virtual Network Operators (MVNO). The key idea revolves around using virtual cache storage resource sharing among MVNOs. That is, storing the most popular video contents at the Base Stations (BSs) to reduce the usage of the backhaul network and, consequently, the delay of users' access. To find the optimal DL model, an RL searching scheme was also proposed to direct the exploration in the direction of models with a better performance. The DL model can be CNNs, RNNs, or Convolutional Recurrent NNs. The architecture is composed of a central controller implemented at the cloud data center and by a slave node located in the BS. The master node searches, selects, and trains the most suitable prediction model. It also collects data and predicts the cache usage and the future popularity of the video content. The slave nodes store the content recommended by the controller and gather usage statistics. The schemes were tested in simulations, showing that the DL model generation engine can create models in an efficient and autonomous manner. The generated models had high accuracy, which reduces network traffic by caching popular video content.

Zhang et al. [74] addressed the problem of controller synchronizations in multi-domain SDNs. They formulated the problem as a Markov Decision Process (MDP) and applied RL in combination with DNN to train a smart and scalable controller synchronization policy, called the Multi-Armed Cooperative Synchronization (MACS). The policy aims to optimize the network performance enhancements provided by the correct synchronization among SDN controllers. DNNs were used in MACS to take advantage of their ability in learning the changing network patterns and maximize the usage of the limited synchronization budget. In the conducted simulations, MACS achieved much higher performance results than the existing SDN controller synchronization algorithms.

Although their capabilities to scale in large scenarios remain to be assessed, hierarchical approaches are predominant in solving the multi-domain management problem in ZSM because, in this kind of solution, local domain agents lack visibility of the whole network, leading to potential problems in path prediction to other domains. Moreover, giving a global network view to these agents is not feasible because of the associated privacy issues that this implies. Apart from that, the error accumulation that occurs when the prediction results are propagated upwards may significantly decrease the system performance [70,71]; thus, mechanisms to control and correct these errors are needed. In this way, some works have focused their efforts on improving the hierarchical learning efficiency [70]. Furthermore, operating ML-based multi-domain architectures is very costly due to the fact that ML models would require too many samples to be trained properly in real time. Finally, RL has emerged as a well-balanced solution for retrieving information on different domains and selecting the best ML model to make the appropriate predictions.

4.3. RAN management

The envisioned coexistence of multiple RATs in future networks requires the development of complex management policies to efficiently operate radio resources. The integration of intelligence in this part of the network permits the design of smart schedulers and managers that will provide high-performance techniques to handle heterogeneous traffic demands.

Ref. [75] proposed an RAN slicing scheme based on an offline RL algorithm that allocates radio resources according to previously observed traffic load changes. The solution was focused on dynamic Vehicle-to-Vehicle (V2V) scenarios. In the designed system, the slicing controller is in charge of executing the RL algorithm, namely Q-learning, based on soft-max decision making for the uplink and downlink of each slice. As explained by the authors, the algorithm operates offline because the online operation could lead to performance degradation, considering that wrong decisions could be made in the exploration process. Thus, the slicing controller operates with a simulated network model that allows the algorithm to evaluate the performance of the considered actions before using them in the real network. The solution was evaluated through extensive computer simulations using MATLAB and showed that the proposed scheme efficiently improves the network performance and outperforms other solutions.

In [76], a DL-based joint pilot design and a channel estimation scheme were proposed. The objective was to apply the technique of minimizing the mean square error of the channel estimation for MIMO channels because there always exists an inter-user interference in MIMO systems, which eventually leads to an increase in the estimation error. The pilot design was constructed with two-layer NNs. The channel estimation was supported by DNNs. All NNs were jointly trained to minimize the mean square error of the channel estimation. They were trained offline by using channel and noise examples generated following real channel and noise statistics. Subsequently, the pilots proved to be non-orthogonal, and the channel estimator was nonlinear. Both mechanisms were evaluated through extensive numerical simulations. Consequently, the scheme significantly outperformed the existing linear estimation solutions. Finally, the scheme was tested with SNR values different from the training ones, proving that the proposed channel estimation method was robust.

Ref. [77] developed an intelligent wireless channel allocation algorithm for high-altitude platform station 5G massive MIMO systems. To provide autonomous learning to the scheme, they combined Q-learning RL and back-propagation NNs. They modeled the channel assignment problem as an MDP and solved it with RL. Massive MIMO communications involve a huge number of connections, and the RL state space increases accordingly. It is difficult to manage this huge space in practice; hence, a back-propagation NN was used to estimate the Q value. In this solution, every Q update is used as an example input to train the network. The system incorporating the proposed solution resulted in an overall performance improvement compared with a random channel allocation.

Ref. [78] proposed a DL scheme for joint channel estimation and pilot signal design applied to two different scenarios of fading, namely quasi-static block fading scenario and a time-varying fading one. They used GANs to generate channel sample data to train the system correctly. In the first scenario, a deep autoencoder based on an FNN and a CNN-based decoder were developed. The autoencoder learns the MIMO channel coefficients while optimizing the pilot signal based on the received SNR feedback. In the second scenario, the scheme operates in the same way, but by combining an RNN and a CNN to learn temporal features more effectively. They also used LSTM to improve the learning of these temporal features. The proposed scheme was evaluated with extensive numerical and experimental tests to demonstrate that it can increase the performance and effectiveness of existing baseline schemes.

Lynch et al. [79] automated the design process of link allocation algorithms for 5G heterogeneous wireless networks using evolutionary learning. The automation through the evolution design procedure saves the costly manual algorithm design effort. The evolved schedulers can only use the link quality reports collected from the system to optimize the controller design in real time. An algorithm for generating schedules in every time slot was also developed to compute the statistical features from the link quality measurements. It then maps these features to an optimized schedule for each cell of the system. Two different model classes were studied, namely, a grammar-based genetic programming model and a fixed-topology NN, whose weights were optimized by a genetic algorithm. The authors evaluated both models by running each one 30 times in a simulated enterprise environment with 12 LTE and eight WiFi cells. The best resulting evolved schedulers were compared on unseen test cases and with baseline heuristics, showing better results in network performance and downlink rates.

In [80], an RL-based distributed channel selection algorithm for massive IoT communications was designed. Given the constraints of IoT devices, the scheme was developed considering minimal memory and computation capabilities. The distributed channel selection problem was considered a multi-armed bandit problem. The objective was to maximize the total number of frames successfully transmitted. In this work, the strategy used to solve the problem was a tug-of-war, a well-known technique to make a series of decisions for maximizing the total sum of obtained RL rewards that frequently change. This strategy was applied to explore the appropriate channel selection by simply checking the reception of ACK frames. That is, the employed channel is rewarded if the device receives the ACK. The proposal was runnable on constrained IoT devices and showed that prototypes could dynamically decide on the best available channel respecting fairness among the rest of the devices.

Politanskyi et al. [81] applied UL in cognitive radio to plan the distribution of free and busy channels. To this end, they developed an algorithm for scanning free and occupied frequency bands to reduce the allocation time and increase the transmission speed in the cognitive radio. The method improved the traditional linear frequency model using a two-dimensional channel distribution. The designed model based on SVMs was tailored to channels that transmit Voice over IP (VoIP) traffic in LTE. The results of the conducted experiments showed that applying this model reduces channel search time by 10%.

Ref. [82] presented a slice admission strategy based on RL. The 5G flexible RAN considered the use case, where services from different providers are virtualized over the same infrastructure. The RL agent was embedded in the orchestrator and trained to manage the slice admission, setup, scaling, tear-down, and reward computation. This strategy aimed to maximize the profit of the infrastructure provider when providing multiple services with different priorities. Therefore, the problem was considered as a loss minimization problem. The RL agent was based on an NN and modeled as a stochastic policy network optimized by applying gradient descent. The optimization algorithm updated the weights of the NN and gradually increased the cumulative reward, converging to a policy that minimized the total loss. In the performed simulations, the designed policy achieved 50% lower loss than static heuristics and 23% compared to threshold heuristics.

Sandoval et al. [83] designed an RL framework that decides which RAT should an IoT node employ when reporting events. The proposed policies considered the global state of the node and aimed to maximize performance while running in constrained IoT devices. The scheme was based on evolution strategies, a type of genetic algorithm. The RL reward was set as the priority of the message multiplied by the length in bits of the packet and divided by the transmission delay. Thus, the nodes took advantage of reporting events as fast as possible. The reward units were bits per second; hence, the reward function maximized the prioritized throughput of a node. Extensive solution simulations were performed by modelling an IoT network with cellular and Long Range (LoRa) networks. The presented approach outperformed other solutions, improving the rewards by 75%.

The ML-based contributions to automate RAN management procedures are mainly based on RL. In this segment of the network, the ML model must rapidly adapt to the changes in the radio medium. This can be achieved with this kind of algorithms occasionally supported by NNs that receive continuous feedback from the medium. However, maintaining the online training of the ML algorithm is difficult in terms of the computation costs due to the ever-changing RAN characteristics. This is why most of the proposed approaches in the literature perform an offline training of the solution that is later embedded into the final device. This approach presents the advantage of using constrained devices as smart objects [84]. The current proposals focus on evolutionary scheduling, radio resource allocation, channel selection, and channel estimation.

4.4. Network resource management

Due to the dispersion of different networks and computing components, resource management in large-scale distributed networks is an intricate challenge. Thus, the failure points in the infrastructure are numerous and difficult to locate in the case of malfunctioning. ML-based monitoring tools can easily learn anomaly patterns and detect, or even predict the fault location. Moreover, NFV has fostered the migration of network functions operating in expensive and inflexible dedicated hardware to software components that run on top of the generic components in the form of VNFs. Nevertheless, numerous challenges arise with this change of paradigm, including the mapping of virtual resources to physical ones. ML-based procedures can easily be in charge of these operations, improving the static solutions commonly used in legacy networks.

Ref. [85] proposed an RL-based VNF performance prediction and placement module to leverage end-to-end performance predictions to automate VNF placement. The architecture of this solution was divided into three layers and comprised the devices, NFV infrastructure, and OSM MANO. Furthermore, the framework included four different agents, namely an application monitoring agent to keep track of the application performance, a node-monitoring agent to supervise the resource utilization of each node, a prediction agent to anticipate the VNF performance and send this information to the OSM MANO, and a placement agent to instantiate VNFs in more suitable locations. The RL approach of the problem uses adaptive Q-learning to predict the total service time of an end-to-end application running VNF video transcoding, which reflects the transmission efficiency and the processing power of the VNF. The solution was tested at the University of Bristol integrated within the 5GINFIRE infrastructure.[17] The experiments showed better adaptability to network traffic changes than models based on SL. In addition, the developed model predicted the VNF performance with 45% more accuracy than SL models.

De Vita et al. [86] designed a DRL model to manage MEC systems without explicit network knowledge. The reference scenario consists of an LTE network, where eNBs are connected to MEC servers used as local repositories. An RL model was developed to deploy a policy that decides when it is necessary to move data from one eNB to another depending on the network state and the user position. The proposed approach included a DNN to predict the Q-values associated with a generic state for the RL algorithm within the RL model. The simulation environment was composed of the MEC LTE network emulated by using SimuLTE and INET simulation frameworks in OMNeT++, and the DRL engine implemented using Keras. In the simulations, the DRL model improved the overall system performance compared to the scenario without any dynamic data migration policy.

Ref. [87] proposed DRL-driven network architecture for automatic routing in SDNs that employs a closed-loop network control mechanism to interact with the network and optimize traffic routing. The SDN controller is connected to the DRL agent and to the forwarding plane. It collects the network status information and generates the flow table rules according to the action indicated by the DRL agent. The traffic monitoring module predicts different traffic flows and applies policies to avoid network congestion. These policies are generated by the DRL agent, which gains experience by interacting with the network in the closed-loop architecture. Once trained, it can achieve a near-optimal routing configuration. The architecture was compared against Open Shortest Path First (OSPF) and Equal-Cost Multi-Path (ECMP) routing achieved good convergence and effectiveness evidenced by packet delay reduction and a network throughput increase.

Kim et al. [88] introduced a dynamic network resource management and adjustment system based on RL. Their proposal was based on the capability of multiple tenants to negotiate with the provider and manage their resource allocation to maximize their profit. The dynamic resource trading system was modeled as an MDP and based on Q-learning. It operated by learning the reward resulting from the previous action while fulfilling the requirements of different traffic flows. The scheme was evaluated by means of comprehensive MATLAB simulations against existing fixed resource allocation methods. The results showed that it could notably increase the tenant's profit.

Ref. [89] presented a DRL network slicing orchestration system. This solution uses DRL to orchestrate the resources of the RAN, computing nodes, and transportation network. A smart agent learns while the system is working on the needs of the network slices and dynamically orchestrates the resources to optimize the performance of end-to-end traffic flows. Therefore, the system also guarantees that the slices meet their corresponding SLA. The virtualization of radio resources was realized by implementing a hypervisor based on Open Air Interface (OAI) that includes new user scheduling methods to match virtual resources to physical ones. The traffic flow bandwidth was handled with SDNs. The computing resources were controlled by a mechanism that manages the number of threads occupied by each user. The prototype was tested and compared with a baseline approach, obtaining a 3.69x improvement.

Raza et al. [90] examined the application of two types of ML algorithms, namely SL and RL, to the slice admission problem in 5G networks. The SL solution was based on big data analytics for processing historical network data for predicting the temporal variations of the resource requirements of each slice. For each request, the SL module predicts the requirements of the incoming slice and rejects requests expected to create resource contentions. The RL agent is modeled as a stochastic policy network that uses an NN to represent the policy. The NN receives an array describing how the resources are used and the request requirements. Consequently, it outputs the probability of accepting or rejecting the slice request. The orchestrator uses this information to decide on the action to be taken. Both models were compared with static approaches. The results showed that using ML significantly reduced the losses of infrastructure providers.

Ref. [91] presented an ML-driven auto-scaling prediction scheme and a service function chain placement model for MEC-enabled 5G networks. Both classification and regression models were proposed to estimate the required number of user plane function instances to ensure that the User Equipment (UE) requirements are satisfied while the network resources are efficiently used. These SL models aimed to identify and exploit the hidden patterns in traffic flows to predict the scaling decisions in advance. The authors also designed an integer linear programming technique to solve the UE association and the service function chain composition. Finally, a heuristic algorithm was developed to address the

[17] https://5ginfire.eu/.

system's scalability. The whole solution was evaluated through simulations. The results showed that both NN-based solutions could efficiently predict the auto-scaling needs of the network. However, the regression model outperformed the classification one in terms of accuracy. Furthermore, the average latency can be significantly reduced by placing the chain functions at the MEC nodes according to their demands.

Ref. [92] presented MAPLE, an ML-based approach for the efficient placement and configuration of VNFs. The solution divides the network of infrastructure providers into multiple clusters to reduce the complexity of the placement procedure. In this way, the hardware and network resource consumption can be efficiently optimized while fulfilling the requirements of different users. The model was based on multi-criteria k-medoid clustering, which divides physical resources into a set of disjoint clusters following certain attributes established by the administrators. A statistical technique was also designed to reduce the clustering time and improve the cluster quality. Finally, relying on this division, an ML-based placement and a readjustment model dynamically adapts the mapping of requested VNFs to the physical resources while ensuring minimal resource waste and improved QoS for users. This last procedure was performed in each cluster only for the subset of the physical network managed by itself. The proposal was evaluated in a realistic environment that considered a large-scale network topology. Compared to migration techniques without clustering, the scheme reduced the CPU usage by 20%, energy consumption by 25%, and bandwidth utilization by 20%.

The HYPER-VINES framework, which is an ML-based framework that detects and localizes faults and performance issues in multi-cloud systems, was presented in Ref. [93]. It aimed to improve the availability and reliability of VNFs in cloud infrastructures. To this end, the framework retrieved performance markers from cloud management platforms over standard interfaces, consequently obtaining large volumes of multi-source and highly dimensional operational data. These data were pre-processed to remove the biases in the processing stage. Afterwards, the produced dataset was analyzed in a two-stage detection subsystem, which first used a shallow ML to eliminate the non-faulting cases and then located and classified the detected fault cases into both imminent and manifested faults using SVMs. The framework was evaluated using a dataset, including real fault logs. The results demonstrated good accuracy and handling of the detection and localization of network impairments and performance issues.

Zhu et al. [94] designed an SL-based QoS assurance architecture for 5G networks. The main function of the system was to use ML to detect the QoS anomalies based on historical data. It can also trigger automatic mitigation procedures or predict future anomalies with high confidence. The 5G QoS-related data were gathered from the KPIs defined in the user equipment and in the access and core network. The data were then pre-processed, cleaned, and transformed into a unified format. A C4.5 DT was used as the SL algorithm to build a model between the QoS data and the KPI parameters. The anomaly detector can spot anomalies in the network, applications, and services. Consequently, it triggered attenuation mechanisms. The architecture was tested with five different traffic datasets and showed more than 96% accuracy in anomaly detection.

Resource management is a wide research field that can be considered from diverse points of view; thus, several ML approaches have been found in the literature. RL is usually adopted to flexibly orchestrate resources along time in closed-loop solutions and give the network the ability to react in real time to the changes in user demands. These mechanisms obtain the necessary network information from diverse monitoring agents, which must be placed throughout the whole architecture. Meanwhile, SL is mainly applied to slice admission, VNF placement, and resource usage prediction because the application of this kind of algorithm enables the development of sophisticated sensing and recognition tasks due to their ability to automatically deal with network complexity, size, and heterogeneity from the resource management point of view. When these ML-based models are applied, high increases in the performance metrics are obtained because resource management in large and distributed networks greatly benefits from dynamic and adaptable policies and decisions.

4.5. Security

The softwarization process performed in the NGNs is bringing a new horizon of possibilities and changes. Many of the traditional solutions adopted in the ossified networks are now obsolete. Thus, the security procedures must be reshaped to cope with the new network paradigm requirements. ML is conceived as the director to lead this shifting by supporting encryption design, access control, authentication, integrity, or confidentiality mechanisms that can dynamically adapt to the changing nature of the envisioned heterogeneous networks.

Furthermore, the relevance of network security is growing each day in our society because of the reliance we have on computer networks and services. Accordingly, the application of ML techniques in ZSM-based security is deeply studied by the scientific community. Several works exploring the application of ML algorithms to different security topics have been presented during the last years [95–100]. Furthermore, numerous surveys covering the state-of-the-art in this area have been published [101–106]. One recent work was presented in Ref. [107], which identified potential attacks to ZSM platforms and possible mitigation measures. Consequently, this field of study has already been exhaustively examined; therefore, the security concerns of the ML-based ZSM remain out of the scope of this survey. We refer the readers to the abovementioned works.

5. Challenges and future lines

This section highlights the main challenges and the future lines to be addressed in the design, development, and operation phases of ML-based ZSM techniques.

5.1. Computation complexity

ML algorithms require a high amount of computation resources to operate, which conflicts with the necessities of ZSM networks because computation efficiency is as important as communication performance [70,75]. The high latency when performing complex operations is incompatible with time-sensitive services; thus, the optimization of ML algorithms is a key factor in NGNs. Moreover, the optimized and intelligent placement of network management functions along with the infrastructure is an open issue that should be tackled to reach a balance between the diverse computation requirements of these functions and the QoS demanded by applications.

5.2. ML model training and maintenance in dynamic networks

The dynamism of traffic flows associated with heterogeneous networks makes it difficult to train and maintain ML models during operation in an efficient way in the long term [66,68]. The state and operating conditions in this kind of network are continuously changing; hence, reactive offline learning cannot cope with traffic fluctuations and the new situations produced by the intervention of ML frameworks. If the system only uses offline learning, the trained models will only be useful and accurate for a limited period of time and for certain known situations. Therefore, online learning has arisen as a promising solution for handling these constant changes [79,83]. To this end, adaptive decision making and ML model adjustments are performed based on the real-time feedback received from the network. Consequently, the system can tune the model parameters to deal with the current traffic flow characteristics.

5.3. Scalability

As studied in the previous section, the deployment of ML-based ZSM solutions is being made in both distributed and centralized manners. The distributed workaround in a MEC-based architecture or in multiple network subsets decreases the latency of communications, benefiting time-sensitive services. However, it may reduce prediction accuracy due to the exploitation of incomplete local information. In hierarchical proposals, error accumulation may also produce a bigger and unintended decrease in the prediction performance [70,71]. In contrast, centralized systems collect global information from the whole network, make better decisions, and provide network optimization. However, this solution depends on the constant collection of information and produces a large amount of signaling messages, which may lead to higher traffic load and synchronization problems. Whether to use a centralized or a distributed solution remains an open problem that should be further studied.

5.4. Cross-layer intelligence

Traditionally, ML has been used in network management services that handle only one protocol stack layer. This limits the potential large-scale intelligence that this kind of algorithm can provide. In heterogeneous networks, the cross-layer cooperation of networking functions currently plays a fundamental role in developing more flexible and efficient solutions [108]. For instance, it can be applied in the RAN to optimize the wireless channel operation by dynamically adapting both the link and physical layers accordingly. Therefore, the exploration of cross-layer solutions will open up a wide variety of techniques that will significantly improve the global performance of ML-based network management frameworks.

5.5. Lack of datasets

ML systems depend on the accessibility to high-quality datasets that permit the training and validation of developed models. The novelty of heterogeneous networks implies the lack of available datasets with the desired characteristics to feed emerging management mechanisms [14, 65]. Moreover, so far in computer communications, exploiting networking data to develop further enhancements is not an extended practice. Consequently, there is a huge need for appropriate network information and statistics collection to enable the correct design and deployment of ML systems. A promising solution to this challenge is emerging through the use of GANs, which learn how to generate new data with the same statistics as a given dataset [109].

5.6. Security

The adoption and spread of ML-based ZSM systems opened a way for new attack vectors in NGNs [9]. The ML algorithms themselves and their hosting frameworks can be disrupted in several ways, severely affecting the network performance. The attacks can affect the data integrity, thereby altering the information collected by the system, which is later used in ML decision making. The system availability is another point of attack by directly striking ML modules and causing malfunctions. Finally, data or user privacy can be compromised by the interception of sensitive information. As usual, security and privacy concerns are fundamental pillars in developing computer systems and must be carefully examined.

6. Conclusions

This work provided a comprehensive overview of the application of ML techniques to the management of next-generation network infrastructures following a ZSM approach. The most important efforts devoted by international standardization bodies were examined. In line with this, foundational ZSM reference architectures were proposed by ETSI and ITU-T to set the groundwork for more advanced ZSM developments. Other working groups within ISO/IEC, IEEE, NIST, and OMG have also been pushing for the development of ML mechanisms for the automated management and orchestration of resources in NGN. Given the recent launch of these initiatives, they are currently in their infancy, and new contributions are expected to in the next months, especially in the fields of security, management interfaces, cross-domain services, and transparency and accountability inside ZSM architectures.

Specific ZSM-related proposals from academia and the industry in the form of international projects or publications were also discussed in this paper. From this dissection, we conclude that ZSM is a hot topic gaining great momentum to further develop and integrate into real NGN deployments. This is evidenced by the number of related ongoing projects and research proposals exploring the ZSM paradigm from different perspectives (e.g., resource orchestration, traffic monitoring, cybersecurity, etc.). However, the integration of ML-based mechanisms within infrastructure management systems brings a series of challenges related to their computation complexity, adaptability, and scalability, which can be important handicaps for reaching the user-demanded QoE levels. Moreover, given the constant evolution of ML, NGNs, and supported applications, new architectural designs and innovative virtualization schemes and management function developments are clearly necessary for enriching the vibrant and rising ZSM ecosystem in the near future.

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.

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