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Integration of Network and Artificial Intelligence toward the Beyond 5G/6G Networks

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SUMMARY Recently, there has been a surge of interest in Artificial Intelligence (AI) and its applications have been considered in various fields. Mobile networks are becoming an indispensable part of our society, and are considered as one of the promising applications of AI. In the Beyond 5G/6G era, AI will continue to penetrate networks and AI will become an integral part of mobile networks. This paper provides an overview of the collaborations between networks and AI from two categories, "AI for Network" and "Network for AI," and predicts mobile networks in the B5G/6G era. It is expected that the future mobile network will be an integrated infrastructure, which will not only be a mere application of AI, but also provide as the process infrastructure for AI applications. This integration requires a driving application, and the network operation is one of the leading candidates. Furthermore, the paper describes the latest research and standardization trends in the autonomous networks, which aims to fully automate network operation, as a future network operation concept with AI, and discusses research issues in the future mobile networks.

key words: *autonomous network, artificial intelligence, beyond 5G, 6G, 3GPP, O-RAN*

1. Introduction

The mobile communication systems grow from a mere communication infrastructure to a livelihood infrastructure and, in the 5th generation mobile communication system (5G) era, a social infrastructure [1]. For sustainable growth, the research and development on beyond 5G (B5G) and the 6th generation mobile communication system (6G) has already begun [2]. The projections of lifestyle in the 2030s lead to the B5G/6G requirements; the reliable communication for mission-critical industrial and lifeline applications [3], the 3D connectivity for drones and flying vehicles [4], the sustainable transformation for impact society and enable environmental footprint reduction [5], and so on. To meet these challenging requirements, while artificial intelligence (AI) is expected as a key technology, its leverage in the networks is identified as an issue to be considered.

AI has recently experienced a surge of interest, and is permeating our lives in areas, such as healthcare, agriculture, finance, transportation, manufacturing, government and public services. The cyber physical system (CPS), a core component of technology concepts such as Industry 4.0 [6] and Society 5.0 [7], accumulates a huge amount of information in physical-space and analyzes this big data in cyber-space to create new value. AI will become an essential component of social infrastructure, and the networks, including B5G/6G networks, must natively support AI, such as high-precision sensing to understand the physical world, transmission of massive big data for training, and optimal distributed computing in networks. In other words, network should be the most efficient platform for AI, driving the evolution from centralized intelligence in the cloud to ubiquitous intelligence at the edge.

Meanwhile, networks become more complex to design, build, optimize, and manage, and it is difficult to do them manually. AI is expected to solve these problems. TM Forum reported that communication service providers would like to introduce new services that require faster and more complex responses from operations than manual processes can provide [8]. ITU-T mentioned that it would be difficult for humans to process it quickly and make a timely decision in controlling networks, and specified the architectural framework with the use of AI [9]. AI is being studied and developed as an aid to both resource and fault management in networks, and will be an essential technology for network control in B5G/6G era.

As mentioned above, collaborations between networks and AI can be broadly classified into two categories: network topology, functionality, and extension for AI-enabled applications, and the use of AI for network analysis, control, and management [10]. The former is referred to as *Network for AI* and the latter as *AI for Network*. These collaborations will not proceed independently, but simultaneously, and it is predicts that AI and networks will eventually be integrated to provide a new integrated infrastructure in the B5G/6G era. Currently standardized AI functionalities in the network cite both user applications and network operations as the use case scenario, and the integration is promised as a future vision. It is natural to integrate two key technology of the social infrastructure, but there is still room for study to make it practical and better. This paper presents recent researches including our activities on the both type collaborations, and discuss challenges for the future networks in the B5G/6G era.

This paper is organized as follows. Section 2 reviews the related works with AI and network collaboration and forecasts the integrated network infrastructure. Section 3 describes autonomous networks as an example of an application that drives this integration and introduces our studies.

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In Sect. 4, the standardization trends related with AI functionality in networks, and Sect. 5 concludes this paper.

2. Network and AI Collaboration

AI is a research area that has received particular attention in recent years, and as shown in Table 1, many studies have been given to collaboration and cooperation with networks. These studies can be broadly categorized as Network for AI, which uses the network as the basis for AI, and AI for Network, which uses AI to enhance the network. This section provides an overview of existing works in each of these areas.

2.1 Network for AI

There is a great deal of interest in using AI to support a range of applications. However, performing AI is challenging because it requires an efficient learning model, a sufficient amount of data, powerful computing environments, and AI expertise [19]. AI as a Service (AIaaS) is increasingly being offered by cloud providers to provide the AI building blocks to support customer applications. These services are intended to be provided on Software Defined Infrastructure (SDI), and it is natural to provide AIaaS on B5G/6G network, as the softwareization and virtualization is a basic trend of network architecture [20]. Multi-access Edge Computing (MEC) is used to offload computing resources and efficiently transport large amounts of data [11]. Processing AI models at the edge, closer to their target, is more effective when combined with fine tuning and transfer learning, which are techniques for adapting AI models to the local environment. Federated learning is a framework for training a deep learning model from decentralized data, and be used in MEC to ensure privacy and security of personal information [21].

Joint Sensing and Communication is technology that integrates sensing and communication using radio waves [22]. It explores radio wave transmission, reflection, and scattering in order to retrieve of interest in the environment surrounding the radio transceivers. These analyses of radio wave are complex and AI-assisted sensing is expected using in-network computing [10].

2.2 AI for Network

It has become difficult to rely solely on the experience and work of operators as networks are used for various applications and permeate society, making them larger and more complex. The study of AI for network design, construction, operation, and management is actively discussed.

AI has shown superior performance to traditional communication theory approaches at the physical layer of wireless communications, and several optimization problems are being considered for application, including non-orthogonal multiple access [13], spectrum sharing [14], and cognitive radios [23]. Since B5G/6G is proposed to use more frequency bands and a large number of base stations, such as massive MIMO, AI optimization of these difficult problem is expected to be used.

As networks become a critical part of social infrastructure, network security is becoming a critical component of maintaining network reliability and resilience. AI is used to identify, mitigate, prevent attacks against networks, e.g., Distributed Denial of Service (DDoS) [15] and malware [24]. The security demand is expected to grow, so the use of AI will become more widespread.

IT systems, including networks, are becoming larger and more complex, making it more difficult for human beings to operate them to perfection. Artificial Intelligence for IT Operations (AIOps) has been proposed to address modern IT management challenges thanks to AI and big data [25]. AIOps is broadly categorized into the failure management, which includes a failure prevention, a failure detection, a root cause analysis, and so on, and the resource provisioning, which includes a resource consolidation, a scheduling, a

Table 1 Studies of network-assisted AI applications and AI-enabled network applications.

Application	Description	Ref.
Network for AI		
Vehicles	Reduce the latency of transferring collected big data through edge computing to provide real-time services to the vehicle.	[11]
Distributed AI	Training AI models on compute nodes distributed across the network for load balancing and cost reduction.	[12]
Sensing	Reduce the Integrated sensing and communication to leverage the large-scale cooperation between widely deployed base stations and user devices for improved sensing performance.	[10]
AI for Network		
Intelligent radio control	Improvement of delay and reliability in radio access network by constellation shaping and interference cancellation.	[13]
Spectrum sharing	Avoiding collision of shared spectrum usage among different operators with a limited amount of information exchanged.	[14]
Network security	Applying artificial intelligence and statistical techniques in the defense methods has been conducted in order to identify, mitigate, and prevent Distributed Denial of Service (DDoS) attacks.	[15]
Fault recovery and analysis	Those networks capable of troubleshooting in an automatic way, making the network more reliable and reducing costs.	[16]
Network operation and maintenance	A low-cost environment that can produce the same data as the actual production environment and use tools such as chaos engineering to generate training models for fault data for network operations and maintenance.	[17]
Data center	Post-mortem diagnosis and proactive prediction of switch failures in a data center network based on syslog messages.	[18]

workload estimation, and so on, each of which is the subject of much research and development. For network operations, AIOps is considered for application to various networks, including mobile networks and data center networks, and the autonomous network that aims to fully automate operations has also been proposed as an all-encompassing concept. For network operations, AIOps is considered for application to a variety of networks, including mobile and data center networks [16]–[18].

2.3 Integration of AI and Network

As mentioned above, much research has been done on the collaboration of networks and AI, and it is expected that the collaboration will be realize in the B5G/6G mobile network on the two aspects, i.e., "Network for AI" and "AI for Network." These two aspects are not independent at all, but have the same requirement that the computing resource for processing AI is contained within networks. This means that B5G/6G mobile networks will evolve from a communications infrastructure to a cloud-like infrastructure that provides communications, computing and storage resources. While the current 5G mobile networks also provide computing resources on MECs, with the advancement of network virtualization, these resource infrastructures will be more tightly integrated.

Since network operation is a critical task for communication service providers and is necessary for the deployment of entire networks, it also seems to be a good application to drive the integration of AI and network infrastructure. Recently, the autonomous network, which aims to fully automate network operation, has been proposed as a future overarching concept. The next section will describe the autonomous network in detail as an example of the AI-empowered application in the B5G/6G era.

3. Autonomous Network

3.1 General Concept of Autonomous Network

The fundamental role of the network is to provide connectivity for communication services and applications. Furthermore, to achieve high quality of service, the network must meet the quality requirements of the services and applications. In traditional network operations, human operators have played this role. Operators install the network equipments, such as WDM systems and IP routers, that constitutes the network, configure them appropriately, and replace them in the event of failures. These critical tasks enable the network to meet these quality requirements around the clock, twenty-four hours a day, seven days a week.

In recent years, there has been a lot of standardization, research and development activities [26]–[29] on Autonomous Networks, where the network autonomously performs these tasks traditionally performed by human operators. As showen in Fig. 1, in the autonomous network,

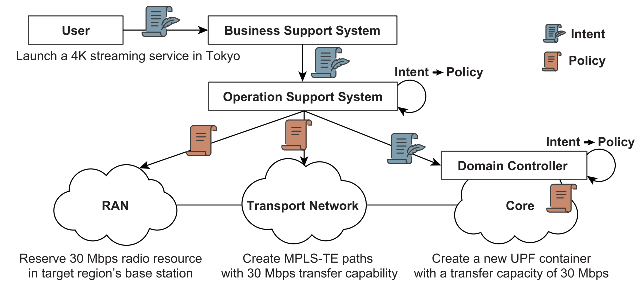

Fig. 1 General concept of autonomous network.

the network's configuration and control are managed autonomously based on Intent information, which represents the requirements of services and applications for the network.

Intent is more abstract information than policy, rules, and logic regarding the network and represents an intention and expectation of the network's user [30], [31]. In the example in Fig. 1, the operational system, which consists of the business support system and the operation support system, receives an Intent from a user who wants to launch a 4K streaming service in Tokyo, translates it into an actual network control policy, and requests it to each network domain. In some cases, Intent may also be sent directly to a domain controller that controls each network domain without being translated into a policy in the operational system. Since the domain controller has a more detailed understanding of the operational data of each network domain, a more detailed and accurate policy translation can be expected. Each domain controller implements control of the relevant network to ensure the quality specified in the policy.

In this manner, the autonomous network models the tasks previously performed by humans and aims to build, operate, and manage networks autonomously.

3.2 AIOps for Autonomous Network

The realization of autonomous networks requires AIOps for several tasks [25], [28]. As described in the above section, in an autonomous network, it is necessary to translate abstract Intent received from users, e.g., "*I want to launch a 4K streaming service in Tokyo*", into concrete policies and rules, e.g., "*Creating MPLS-TE paths with 30 Mbps transfer capability*". Intent allows different users to author the network services in a form that a particular constituency of users understands, without having to use a language that they do not normally use, such as a programming language [32]. However, user Intent varies widely, making fixed, traditional rule-based translation difficult. The remarkable advances in the natural language processing AI model are establishing to extract Intent from natural language and conversation [33]. The interaction between a user and AI are useful not only for understanding the user's needs, but also for negotiating with the user, for example negotiating when network resources are insufficient. As described in Sect. 2.2, AIOps is expected to be applied to critical elements of network operations such as resource provisioning and failure management [25]. Therefore, with AIOps and Intent, new networks can be created, and network failures can be handled automatically without human operators, which realizes autonomous networks.

Network management is another task where AIOps need to be applied. Each domain controller manages the network to meet the key performance indicators (KPIs) or the key quality indicators (KQIs) specified in the policy. KPIs include the available bandwidth, packet loss rate, latency, device availability, and so on, and when the network falls below the KPIs, which is defined as a "network failure", the domain controller will take appropriate action. Fault recovery must be carefully considered for both humans and AI, as incorrect actions may exacerbate the network failure. Closed loops consisting of observation, analysis and control help to validate recovery workflows, i.e., monitoring KPI/KQI changes due to the recovery actions, not only in the whole network but also in the each domain, can quickly detect incorrect actions and prevent them from becoming critical failures. Network virtualization or softwareization, which is a essential trend of modern and future network, is also useful for realizing the autonomous network, enabling software-based actions such as rebooting the failed device and building new instances of network equipment. This feature not only simplifies recovery actions, but also makes it possible to revert to the state before the action was applied.

3.3 Network Failure Management by AIOps

Within the expected areas of AIOps, we have proposed an integrated framework, illustrated in Fig. 2, for network failure management, including anomaly detection [34] and fault recovery functions [35]. The framework has two phases: the AI model training phase for AIOps and the AI model inference phase from actual operational data.

Firstly, in the AI model training phase, AI models are trained from operational data, such as CPU utilization rate and trouble tickets, obtained in the target network. Since network failures are infrequent events in production networks, sufficient operational data for AI models may not be obtained. Therefore, to train precise AI models, a test network simulating the production network can be created, and operational data obtained from pseudo network failure generated

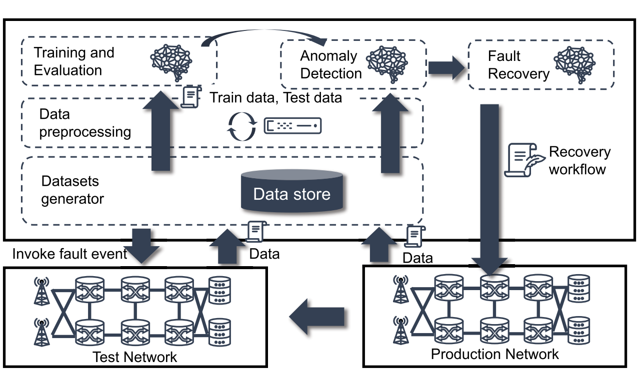

Fig. 2 AIOps framework for network failure management.

in the test network can be utilized as input data for the AI model.

Secondly, in the AI model inference phase, the trained AI model detects a root cause of network failure from the latest operational dataset and suggests an optimal recovery workflow from the network failure, with anomaly detection and fault recovery function. The fault analysis function detects network failures and determines their root causes.

Within this framework, we have evaluated a comparative experiment that involved measuring the performance of the fault analysis function using three AI algorithms, multi-layer perceptron (MLP), random forest (RF), and support vector machine (SVM), on the testbed network built by the virtualized network functions (VNFs) [34]. RF showed the highest accuracy, and F1 scores for three network failures: compute node down, network interface down and CPU overload were 1.00, 0.96, and 0.95, respectively. This difference in accuracy by AI algorithms is likely due to the dataset generated from the performance management (PM) data, and the increase in training data, feature reduction, or balance adjustment of normal/abnormal samples effected the accuracy.

Furthermore, we have proposed a scheme for fault recovery using reinforcement learning (RL) [35]. The scheme can adapt to changes in network topology and configuration, and has a data representation procedure to prepare a data set for RL, which is formed as a matrix of network topology and fault state. The simulation results showed that it requires a tremendous amount of failure injection and recovery operation trials to prepare enough training data. The test network simulating the production network has a potential to shorten the time for trials in the training process, but it was clear that showed that the behavior between the test network and the production network infrastructures should be 87% coincident for application to the proposed scheme.

While AI is expected to be utilized in various tasks of network operation in the autonomous network, there is still room for research on AI algorithms and schemes for each task.

4. Specifications of AI Functionality in Network

AI promises to assist network operations, and frameworks for AI-empowered network operations have been standardized. This section introduces standardizations of AI functionalities in the 3GPP [36] and the O-RAN Alliance [37] for mobile core network and radio area network (RAN), respectively.

4.1 Network Data Analytics Function

The most recognized AI functionality in networks is the network data analytics function (NWDAF) in mobile core networks. The NWDAF refers to a network function specified in Clause 6.2.18 of 3GPP TS 23.501 as a part of the architecture for the 5G system, which includes one or more of the following functionalities [38].

- Support data collection from network functions (NFs)

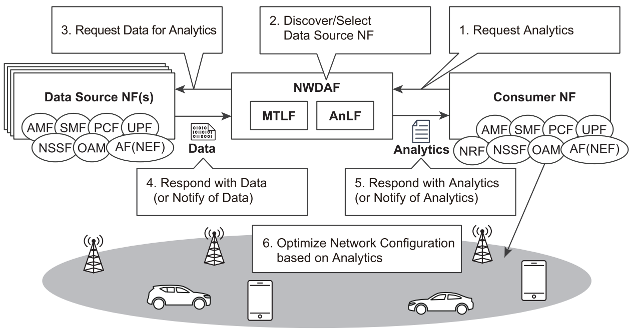

Fig. 3 Generic information flow of NWDAF.

and application functions (AFs)

- Support data collection from operations, administration and management (OAM)
- NWDAF service registration and metadata exposure to NFs and AFs
- Support analytics information provisioning to NFs and AFs
- Support machine learning model training and provisioning to NWDAFs (containing analytics logical function)

The detailed specifications of NWDAF are defined in 3GPP TS 23.288 [39]. The main objective of NWDAF is to optimize the network configuration based on analytics. The generic information flow is extracted as depicted in Fig. 1, which is commonly applied to all analytics defined in the specification. The information flow involves three functional blocks, i.e., NWDAF, consumer NF, and data source NF, and consists of the following steps. Any NFs in the mobile network possibly be the consumer NF, and any AFs can also be the consumer regardless of their trust.

1. Consumer NF sends a request for analytics (or for a subscription to the analytics in the case of subscribe/notify model).
2. NWDAF discovers or selects the appropriate data source NF(s) based on the request by asking network repository function (NRF).
3. NWDAF sends a request for data (or for a subscription to the data).
4. Data source NF(s) responds with the requested data or notify of the requested data. Note that how data source NF(s) observes or collects data is out of the scope of the specification.
5. NWDAF responds with analytics (or notify of analytics).
6. Consumer NF optimizes the network configuration based on the analytics. Note that how the consumer NF optimizes the network configuration is out of the scope of the specification.

For the moment of the beginning of Release 18, 14 analytics, such as "*Slice load level related network data analytics*", "*Observed Service Experience related network data analytics*", and so on, have been specified so far. The upcoming versions may introduce further analytics. Most of the analytics support the prediction as well as the analysis of past data. AI is especially expected to facilitate fast and accurate prediction.

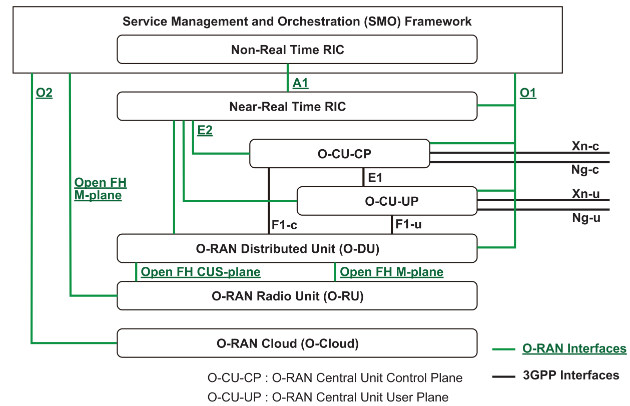

Fig. 4 O-RAN architecture overview.

As for the latest update in Release 17, mobility of the analytics, that means transfer of analytics context from one NWDAF to another NWDAF, and aggregation of multiple analytics are newly supported. Additionally, to enhance AI-friendly architecture, NWDAF has been logically split into two logical functions, i.e., Analytics logical function (AnLF) and Model training logical function (MTLF) are also newly introduced. AnLF is in charge of providing analytics services to consumers, and MTLF is in charge of training machine learning models and delivering models to AnLF. This logical split has evolved into a mechanism that facilitates the operation and execution of various AI algorithms including federated learning. As an extension of the enhancement of Release 17, AI functionality in the mobile network will be further advanced in the upcoming Release 18 and later versions.

4.2 Non-Realtime RAN Intelligent Controller

Figure 4 shows an overview of the O-RAN architecture [40]. The O-RAN Alliance describes a non real time RAN intelligent controller (Non-RT RIC) as a functionality of the service management and orchestration (SMO) to realize intelligent RAN optimization. The main task of Non-RT RIC is service and policy management, such as providing policy-based guidance, AI model management, and enrichment information to the near real time (Near-RT) RIC functions. The Non-RT RIC also intelligently manages radio resources in a non-real time of greater than 1 second, as it is named, while a Near-RT RIC works in real-time. Non-RT RIC creates policies that specify quality of service (QoS) and quality of experience (QoE) targets or KPI/KQI targets, such as guaranteed flow bit rate, priority level, mean opinion score (MOS) value, or throughput and latency for specific user equipments (UEs), slices, QoS flows, and cells and transfer them to Near-RT RIC over the A1 interface. The RIC can determine the RAN optimization actions and configuration by AI/ML training and data analytics, where the data, such as radio resource allocation parameters and UE performance report, are collected from RAN by the SMO over the O1 interface. O-RAN Alliance also discusses a use case of automation in which AI predicts traffic demand using such a framework, and RIC re-allocates network resources before congestion occur.

4.3 Network Functionality Exposure

The main object of these standardized functionalities described in the above sections is the intelligent network optimization and only partial optimization is showed as a use case. TM Forum defines six levels of autonomous networks, and shows advanced or fully autonomous networks beyond partial optimization [26]. In the B5G/6G networks, the network operators will have the huge turning point to AI-driven network operations, i.e., the operators does not maintain the network, but maintain the AI models for the network management.

At the same time, the idea of exposing access to network functions as application programmable interfaces (APIs), and leveraging them inside and outside organizations to expand the ecosystem, is also gaining traction as the "API economy". The network exposure function (NEF) in the mobile core network exposure NF capabilities and events for 3rd party, application functions, edge computing, and so on. CAMARA is a open source project to define, develop and test the APIs to access telco networks [41]. The activities facilitate application-to-network integration, and may also realize the integration of networks and AI when AI becomes part of the functions in B5G/6G networks.

5. Conclusion

Mobile networks have evolved from mere communication infrastructure to the foundation of our lives and social activities, and their affinity with various applications will solidify their position in the B5G/6G era. AI is another technology that can be applied to various applications and is expected to make significant progress in the future. The fusion of these two foundations is a natural progression and is expected to progress further in the future.

This paper introduced these efforts from both "Network for AI" and "AI for Network" perspectives, and mentioned the autonomous network as a comprehensive concept of "AI for Network." Since 3GPP and the O-RAN Alliance standardize network frameworks and functions for AI-enabled network operation, i.e. Network for "AI for Network", AIOps will become a key technology for network operation in the B5G/6G era.

However, there is still room for research and development to achieve the high accuracy required by commercial networks. Networks change on a daily basis, and there are issues such as how to keep up with these changes and how to build an AI model to operate a new network offering a new service. In addition, the autonomous network may change the role of operators; instead of operators directly operating the network, they will operate AI models that operate the network. The skills required at that time may be higher than today. The use of AI is an inevitable and essential matter in the future, and these issues need to be carefully addressed.

We believe that this paper will help researchers in networking and AI to understand the current status and challenges and contribute to the creation of new technologies in the future.

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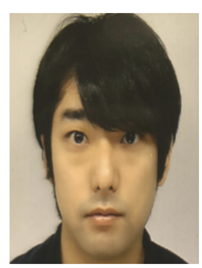

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