Evolved NWDAF Towards a Fully Distributed Artificial Intelligence in the 6G Network Architecture

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Abstract. *Artificial Intelligence (AI) is essential for evolving mobile networks towards 6G technology generation and beyond. In this context, the 3GPP has incorporated the Network Data Analytics Function (NWDAF) at the network's core to leverage network data analytics, focusing on using analytics for automation. However, although NWDAF represents a significant advancement in this area, there is no consensus on deploying AI in the 6G network. This work suggests a framework for developing NWDAF that includes the necessary interfaces and behaviors to enhance the core network with AI capabilities Beyond 5G (B5G) and 6G networks. By analyzing existing literature, we identify a set of potential research directions and propose and suggest a hybrid approach to integrate AI across the entire network using a new distributed network function called Evolved Network Data Analytics Function (eNWDAF).*

1. Introduction

AI is an essential key for evolving mobile networks towards 6G technology generation and beyond [Wu et al. 2021] by leveraging important capabilities, e.g., infrastructure and network automation, traffic real-time performance analysis, and slicing orchestration in the data plane and improving management in the control and management planes [Hernández-Chulde and Cervelló-Pastor 2019].

To provide analytics services in the mobile networks, the 3GPP launched a specific network function, the NWDAF [3GPP 2019a]. The 5G specification initially proposed and integrated such a function with several others. Its main objective is to collect data from these other functions and provide analytics services by evaluating them. Although some researchers profess that the NWDAF is the function responsible for AI and Machine Learning (ML), it was not initially designed for this, being restricted to analytics services. Nevertheless, it is a proper starting point [Wu et al. 2021].

Most existing work in the literature focuses on the Radio Access Network (RAN) segment, and almost all of them are divided between two approaches, which are centralized or distributed. The choice of an approach allows the deployment of AI, ML, and analytics services targeting specific contexts, such as network performance analytics, User Equipment (UE) related analytics, errors and abnormal behaviors, etc. However, the fundamental difference from 5G to 6G regarding AI is the omnipresence of intelligence through the whole architecture. In this scenario, how will the development of AI based services in the 6G architecture?

In this work, we evaluate some start-of-the-art proposals considering the omnipresence of AI, type of learning, data origin, architecture, and compatibility with the 3GPP NWDAF. Sequentially, we explain the advantages and disadvantages of centralized and distributed approaches and suggest a hybrid approach to integrate AI across the entire network. Unlike other works, ours did not focus on one specific segment, e.g., RAN, transport, or core. We introduce the eNWDAF, which is an evolution of 5G NWDAF to move this network function from an analytics services function to a complete AI solution without losing the compatibility with the 3GPP existing interfaces and integration.

The remainder of this work is organized as follows. In Section 2, we give a survey of the related work based on five criteria topics. In Section 3, we present a rationale for our approach by comparing three possible research paths for the subject. In Section 4, outlines our proposed solution, termed eNWDAF, and elucidates the role of AI within the 6G network architecture. Finally, in Section 5, we pose our concluding remarks and discuss possible directions for future work.

2. Related Work

This section presents an overall scenario of how the research community envisages AI/ML capabilities inside the 6G network architecture. Table 1 summarizes the works evaluated. The table describes some key aspects of this analysis.

The *AI/ML Across Architecture* column shows whether AI algorithms are applied across the entire network architecture (end-to-end) or only in a certain segment (such as RAN, transport, core). It should be noted that, although some works claim their solution is end-to-end, the AI algorithms in these works only work with RAN data. The *Learning Type* column shows the learning methods that the works considered in their solutions and experiments, such as supervised learning, unsupervised learning, etc. The *Data Source* column shows where the data that supports the technique is collected from, for example, RAN, core, network functions, UE, among others.

The *Type of AI Architecture* presents how AI architecture is deployed from the 6G core point of view: centralized or distributed. These are the two most common approaches to implementing ubiquitous AI capabilities in 6G.

Finally, the *3GPP Compatible* column shows the current status of each work concerning 3GPP releases. The information *No* in this column needs to present apparent compatibility with 3GPP releases.

Some Works proposes a possible hybrid architecture to support AI. Some of these works have data analysis functions separated by the domain (RAN, core, edge), while the decision-making module is centralized [Abbas et al. 2022]. For these works, it can be

Table 1. State of the art about AI in the 6G architecture.

Reference	AI/ML across the Architecture	Type of Learning	Origin of Data	Type of AI Architecture	Compatible with 3GPP?
[Sevgican et al. 2020]	RAN	Supervised	RRU, UE	Centralized	Yes
[Jeon et al. 2022]	End-to-end	Federated	All NFs	Distributed	Not
[Hernández-Chulde and Cervelló-Pastor 2019]	Not specified	Supervised, Not supervised, reinforcement learning	Not specified	Distributed	Based on
[Chouman et al. 2022]	End-to-end	Federated Learning	All NFs	Distributed	Yes
[Aarna Networks 2022]	End-to-end	Supervised, Not supervised	Data lake/ warehouse, NFs, OAM	Distributed	Yes
[on5g.es 2022]	Not specified	Not specified	Not specified	Not specified	Yes
[Samdanis and Taleb 2020]	End-to-end	Not specified	All NFs, including not 3GPP	Centralized	Yes
[netscout.com 2022]	End-to-end	Not specified	Not specified	Centralized	Yes
[Abbas et al. 2022]	End-to-end	Supervised (Algorithms Ensemble Learning, GBM, XGBoost, CatBoost).	RAN, edge, core	Distributed with some centralized components	Yes
[Aumayr et al. 2022]	End-to-end	Supervised and Not supervised (in the future)	RAN, edge and core	Distributed	Yes
[Liu et al. 2022]	End-to-end	Not specified	Not specified	Centralized or distributed	Based on
[Barmpounakis and Demestichas 2022]	Edge	Federated	Not specified	Centralized or distributed	Not
[Shehzad et al. 2022]	RAN (PHY Layer)	Supervised, Not supervised, reinforcement learning	RAN	Out of scope	Yes
[Wu et al. 2021]	End-to-end	Multi-agent learning (including reinforcement learning)	RAN, CN, TN	Centralized or distributed	Not

said that components that execute algorithms are distributed and not just data collection components. Centralized components receive data from domains and can integrate with 3GPP components, such as NWDAF [Abbas et al. 2022]. Since there are specific components in all domains, it can be considered that works of this type allow for end-to-end AI coverage.

The work presented by [Wu et al. 2021] proposes an evolution of functions designed to support voice, data, and intelligence, the latter of which begins in 5G with the introduction of NWDAF and permeates the final network. to a future evolution of the 6G architecture. The article proposes the concept of "*intelligence inclusion*" as a high-level abstraction for a premature vision of how 6G will natively support AI services.

This *intelligence inclusion* minimally incorporates four application aspects within the 6G architecture: infrastructure, data governance (mainly related to data privacy and security), Network Operations, Administration and Maintenance (OAM), and third party AI services [Wu et al. 2021].

To make this architecture viable, the authors propose some new functionalities in addition to the data and control planes: a new intelligence plane (*intelligent plane*) and a Everything as a Service (XaaS) platform that can integrate infrastructure, communication, and computing at the Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS) layers.

The work presented by [Chouman et al. 2022] analyzes technical details about the implementation of the NWDAF component, as well as its integration into a functional 5G Core based on the Open5GS implementation [Open5GS 2022] and the UERANYes emulation tool [Aligungr 2023]. This work explores a case study that applies NWDAF in MANO to optimize the provisioning of network functions. The data and statistics of the Core functions are accessed directly by NWDAF via SBA, which analyzes the protocols used and the size of the primitives. These results are made available by one of the services defined by the NWDAF specification and can, therefore, be integrated into MANO.

The work presented at [Abbas et al. 2022] proposes a platform based on the concept of *Intent-based Networking* to provide intelligent control and management of network slices with functions specified by 3GPP for the NWDAF component, which is used for slice utilization prediction, QoS guarantee, load balancing, automatic scaling of VNF resources and anomaly detection. The results presented are preliminary but point to the feasibility of using NWDAF to design an Intent-Based Network (IBN) approach.

In [Jeon et al. 2022], the authors present a proposed distributed architecture where each core function is associated with an NWDAF (called leaf - *Leaf NWDAF*) that contains the analytical models associated with each core function. In the architecture, there is also a central NWDAF (called *Root NWDAF*) that is responsible for training the models of each *Leaf NWDAF*. The Root NWDAF has a communication module to update the models on each *Leaf NWDAF*. Despite the view of components distributed across functions, all of these components are deployed in the network's core.

3. Possible Paths for AI Integration

The 3GPP and ITU specifications regarding AI for 5G can be considered emerging [Wu et al. 2021, Sevgican et al. 2020] and preliminary efforts towards smart network fully assisted with AI [Koufos et al. 2021]. NWDAF appeared in Release 15 [3GPP 2019b], further detailed in Release 16 [3GPP 2019a] and is evolving by adding new components to the architecture [3GPP 2023].

In this section, we examine the potential deployment of AI within 6G networks and discuss possible pathways regarding the role of AI in the 6G architecture. We delineate three distinct approaches to achieve this: centralized, distributed, and hybrid.

3.1. Path 1: Centralized

Our initial investigations showed that the natural trajectory for AI deployment could lean towards a distributed approach, especially given the precedent of AI at the network edge within the specification of 5G networks. Surprisingly, however, we discovered a contradictory trend, as most work we evaluated relied on centralized NWDAF components.

We believe that the centralized approach was adopted for two main reasons: (i) the focus of the work on machine learning techniques and models, and (ii) the emphasis of the work on the RAN segment. The first reason implies that, due to the lack of specification of NWDAF internal components, the works inherently applied AI and focused on defining datasets and AI algorithms rather than the architecture. The second reason is that, although some works mention that their proposals encompass all network segments, the experiments and simulations primarily target the RAN segment in practice.

The main advantages of centralized AI are ease of implementation and deployment, data security (from the point of view of implementing security mechanisms), and the possibility for researchers to spend more effort on AI algorithms than on setting up the environment. In general, even operating in the RAN segment, proposals send data to public or private clouds where the AI components are located. Due to the low learning curve of the cloud, implementation and deployment efforts are considered low since the data is centralized and stored. The security concern of the collected data is minimized, that is, concerns about security in a single location. Finally, many AI jobs in computer networks and telecommunications are primarily concerned with learning and analyzing data for security, handover, and traffic control, among others, which means that most of The researchers' concern lies in the AI algorithms and preparation of datasets. A basic setup was considered sufficient in most work.

The main disadvantages of centralized AI are high network traffic for sending data collected throughout the topology, universal data processing, data security (from a risk point of view), and high delay. High data traffic increases the cost for operators and infrastructure providers and increases the time complexity of data analysis. Since the data is processed in the same place, although it is not mandatory, AI can be induced to treat the data in the same way, and data from different segments must be treated considering the particularities of the segment in question. While implementing data security mechanisms in a single location offers certain advantages (as explained in the preceding paragraph), the associated risk is more pronounced than in a distributed environment. This heightened risk arises because if an attacker successfully breaches the security mechanisms, they would gain access to data spanning the entire topology. Moreover, the potential delay in transmitting metrics, considering the long round-trip times expected from the furthest nodes in the network to the NWDAF component deployed in the core, can pose challenges to the centralized approach.

3.2. Path 2: Distributed

Most state-of-the-art works argue that AI is end-to-end. A distributed solution is consistent, as specific AI components for each segment can be implemented. In this sense, the distributed path means that the application of AI should be distributed throughout the topology and not just the information collection.

The main advantage of distributed AI lies in the application of appropriate AI techniques and models for each segment. For example, an algorithm for RAN has different inputs and outputs than that for Transport Network (TN). The data to be trained, classified, and analyzed vary from segment to segment. Another advantage of distributed AI is the processing power and data transfer traffic: processing can be distributed across different network segments, and data do not need to be transmitted between segments at all times, thus saving bandwidth. Finally, reducing delay is an advantage since AI procedures are executed locally.

The disadvantages of a distributed approach are the complexity of deploying components throughout the topology and unifying results for end-to-end applications. Despite this, the centralized approach seems suitable for research projects focusing on AI techniques, but in productive environments of large operators and corporate companies, it becomes an unsustainable approach. The unification of results is a problem because the proposals call for end-to-end but do not make clear how specific metrics from a given segment affect other segments. For example, in the TN segment, a metric related to the latency of a given link is essential. But, in Core Network (CN), this metric makes no sense if it is not correlated to a CPU, memory, etc. metric. This way, results from applying AI in a given segment tend to improve resource management.

3.3. Path 3: Hybrid

A hybrid approach is adopted in some state-of-the-art works. Typically, certain components are deployed across various segments such as RAN, TN, and CN, while others are centralized and integrated into a centralized NWDAF. This approach entails distributing collection components and processing components across different segments. In [Abbas et al. 2022], centralized components analyze data from various segments to discern user intentions.

We believe the hybrid approach combines the most beneficial aspects of centralized and distributed approaches. This approach minimizes data traffic since not all data needs to be transmitted to centralized components. Processing tasks can be distributed across different parts of the topology. Moreover, the specific characteristics of each segment can be managed within the segment itself, while end-to-end AI can be implemented within centralized components.

Notably, each approach, whether centralized or distributed, offers explicit advantages. For instance, consider data traffic: in the distributed approach, traffic remains lower compared to the hybrid approach since no data exchange occurs between different segments or components, as in the hybrid approach.

However, in light of concepts such as federated learning and transfer learning, the hybrid approach facilitates the execution of AI algorithms in various threads, akin to the distributed approach and within the core itself, resembling the centralized approach.

Consequently, data confined to specific regions can be processed locally, and training data can be repurposed for alternative training tasks.

Therefore, it becomes apparent that the use of the hybrid approach facilitates federated/transfer learning. Moreover, it can be argued that achieving federated learning within a centralized environment is practically unfeasible or highly complex. Additionally, it can be asserted that transfer learning necessitates at least centralized entities to orchestrate the training algorithms' input, output, and transformations.

3.4. Comparison and Determination of Preferred Path

Considering the investigation carried out, we have foreseen two main open challenges. The first is that most works address the end-to-end aspect and mention that the solution considers all network segments; however, in practice, we find experiments and simulations focusing only on RAN. The second challenge is the correlation of data from different segments, that is, how data from the TN segment (for example, link usage) is related to data from RAN (for example, propagation delay in the antenna) or with CN data (for example, memory capacity), and so on.

A hybrid path is preferred to attack the two open problems. In this way, AI components can be experimented on different network segments in a distributed manner, focusing on different segments of the RAN (contrary to what is commonly found in the literature). Also, centralized components can be designed with functionalities for correlating data from different segments.

4. Evolved NWDAF with a Hybrid Approach

To follow the hybrid path, we started by enhancing the functional specification of the existing 5G core, depicted in Figure 1. This specification shows that the functions necessary to operate the mobile connectivity service remain with an additional proposed entity NWDAF with a dual role. Initially, 3GPP understands that NWDAF fulfills the role of offering analytics to the network, for which both AI and data aggregation techniques are necessary. However, we are working with the hypothesis of extending this understanding from an analytics function at the core to an entity that offers artificial intelligence on demand, both for the operation and management of the network, as well as for users and new applications.

Therefore, as illustrated in Figure 1, two roles for NWDAF are distinguished: AI for Connectivity, indicated as *AI for Networking* and Connectivity for AI, denoted as *Networking for AI*. The eNWDAF is a functional evolution for NWDAF, when compared to the most recent (Release 18) designed by 3rd Generation Partnership Project (3GPP).

The term AI for Connectivity refers to using AI techniques to support the operation and management of the network in its most diverse aspects.

To this end, it is envisioned that AI paradigms can be widely used, for example, in traffic prediction, optimization of resource use, and improvement of security mechanisms. The need for an entity performing this role is based on the fact that the use of AI techniques known today are foreign to network architecture. In this sense, new AI capabilities can placed as additional functions in the network and not as a fixed set of procedures for analytics exposure, as presented in the latest 3GPP Release [3GPP 2023].

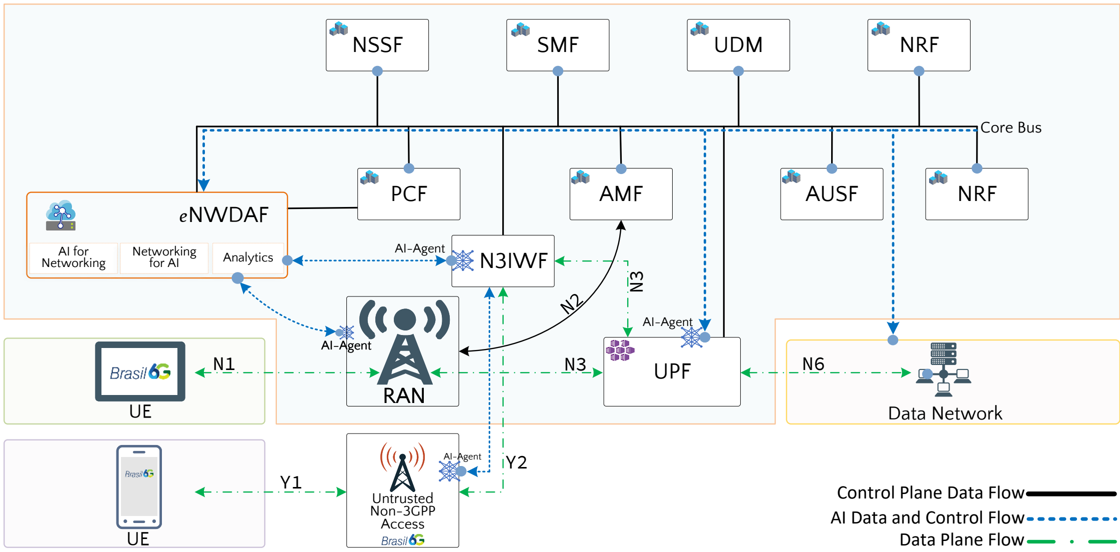

Figure 1. Advances in Core Related to AI the eNWDAF in the 6G Architecture.

This leads to limitations when multiple AI paradigms and techniques coexist on an architecture, which limits end-to-end and detailed management. Alternatively, with an entity fulfilling the role of dealing with AI techniques to support connectivity, problems like this can be addressed.

Another role envisaged for eNWDAF is a native AI support entity that can provide information to applications and users. In this case, the network can help applications to have greater awareness of the context relative to the network that supports them. This is the concept of Networking for AI.

The design of an entity with this role advances the concept of analytics initially understood and accepted by 3GPP, and above all, it places the network core as an ecosystem to support users and intelligent applications, locally consuming computational resources to support AI. The reason for this role assigned to eNWDAF is to introduce the concept of edge computing into the core of the mobile network, incorporating computational capabilities and the provision of sophisticated services in the core of the mobile network to offer AI, with its consequences and paradigms for users.

The element called Artificial Intelligence Agent (AI-Agent) is responsible for the hybrid deployment of AI throughout the network topology. This element has two main functions. The first concerns implementing AI techniques and mechanisms through various processes such as training, learning, and inference. The other function is related to the transfer of data necessary for both the operation and management of these distributed AI mechanisms throughout the network topology and its architecture.

The hybrid technique devised in this work extends the expected capabilities of the NWDAF entity by making it support the dual operation of the AI mechanisms. On the one hand, we envision the offering and delivery of AI functionalidata collectionnetwork architecture, fulfilling all the demands of the life cycle of network slices and monitoring. Furthermore, we idealized a distributed operation, that is, based on AI-Agent, which are code routines distributed throughout the architecture. These routines allow both the collection of data for the analytics mechanism and to carry out known AI functions, that is, prediction, classification, and forecasting.

The other innovation designed for eNWDAF is the realization of native AI support for applications and users. With this, it is expected to offer AI services in a disruptive way, an alternative to the standard centered on high-performance servers.

5. Concluding Remarks

This study explored the feasibility and methods for integrating Artificial Intelligence (AI) functionalities in a hybrid approach into the emerging 6G network architecture. The research highlighted the evolution of AI capabilities, focusing on different machine learning methods applied throughout the entire network architecture, from the RAN to the core segments.

According to recent studies, implementing AI in 6G networks using a fully distributed approach is feasible and advantageous regarding scalability, security, and resource management efficiency. AI systems can be effectively integrated with functions at all network levels by applying diverging techniques, e.g., supervised, unsupervised, and federated learning.

Moreover, the research about centralized, distributed, and hybrid architectures showed that, although the centralized method is simpler and easier to implement, it has some significant drawbacks regarding data security and latency. On the other hand, the distributed architecture provides more flexibility and robustness by distributing the processing load and reducing the risks associated with data centralization.

Finally, implementing a hybrid approach, which combines the best aspects of centralized and distributed architectures that evolve the NWDAF concepts, was identified as a promising solution to overcome technical and operational challenges. This hybrid path balances efficiency, security, and innovation, becoming a viable strategy for advancing 6G networks. In future work, we will detail the eNWDAF components structure and behavior and present an experimental evaluation to showcase AI for Networking and the Networking for AI capabilities.

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