Journal of Electrical Engineering and Information Technologies, Vol. **9,** No. 1, pp. 33–41 (2024)
Article 217
Received: November 16, 2023
Accepted: December 25, 2023
In print: ISSN 2545–4250
On line: ISSN 2545–4269
UDC: 621.395.721.5:004.77]:[004.8:620.92-027.236
https://doi.org/10.51466/JEEIT2491217033k

Original scientific paper

ENERGY EFFICIENCY IN 6G MOBILE NETWORKS

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A b s t r a c t: The 5G network technology is finding its use in variety of sectors in the global industry. Significant improvements are achieved in terms of latency, data rates, spectral efficiency, mobility, and number of connected smart mobile devices. Digital society and smart cities are reality. 5G networks offer a wide range of applications and services, but still have some limitations regarding the rapidly increasing data traffic demands. The focus of the research and development activities are set on the next 6G mobile and wireless networks, which are expected to be commercially available around 2030. In this direction, this paper proposes a 6G Advanced Wireless Mobile Heterogeneous Access Network (6G AWN-HAN) architecture with artificial intelligence, whose description is expected to contribute in defining the specification standards of 6G network. It also evaluates the performance quality of artificially intelligently, orchestrated services in 6G mobile networks in terms of energy efficiency. The research results show a significant improvement in energy efficiency by applying artificial intelligence at the edge of the network.

Key words: 5G; 6G; artificial intelligence; Internet of Things

ЕНЕРГЕТСКА ЕФИКАСНОСТ ВО МОБИЛНИ 6G-МРЕЖИ

А п с т р а к т: Мрежната 5G технологија ја наоѓа својата примена во различни сектори од глобалната индустрија. Постигнати се значителни подобрувања во однос на латентноста, брзините на пренос на податоци, спектралната ефикасност, мобилноста и бројот на поврзани мобилни уреди. Дигиталното општество и паметните градови се реалност. 5G-мрежите нудат широк опсег на апликации и услуги, но сепак имаат одредени ограничувања во однос на рапидното зголемување на барањата за сообраќај на податоци. Фокусот на активностите за истражување и развој е поставен на следните мобилни 6G-мрежи, кои се очекува да бидат комерцијално достапни околу 2030 година. Во таа насока, овој труд предлага архитектура на напредна безжична мобилна хетерогена пристапна 6G-мрежа (6G AWN-HAN) со вештачка интелигенција, чиј опис се очекува да придонесе за дефинирањето на спецификациите на стандардот за 6G-мрежата. Исто така се евалуира квалитетот на перформансите на вештачки интелигентно оркестрирани услуги во мобилните 6G-мрежи во смисла на енергетската ефикасност. Резултатите од истражувањето покажуваат значително подобрување на енергетската ефикасност со примена на вештачката интелегенција на работ од мрежата.

Клучни зборови: 5G; 6G; вештачка интелигенција, интернет на нештата

1. INTRODUCTION

5G mobile and wireless networks achieved significant improvements in terms of latency, data rates, spectral efficiency, mobility, and number of connected smart mobile devices. Therefore, they have marked the beginning of a true digital society.

Nowadays there is a shift towards a society of fully automated and remote management systems in number of business sectors and industries. The rapid development of artificial intelligence (AI), virtual reality, three-dimensional (3D) media, and the Internet of Everything (IoE), has led to a massive volume of traffic [1]. The global mobile traffic in 2030 is predicted to be around 5000 EB/month [2].

However, up to the present moment, 5G mobile communications have so far provided little added value for consumers due to the high cost of the services, and inadequate availability (especially in rural areas). In addition, 5G requires more transmission antennas for uniform network coverage than 4G network.

Although 5G network offers support of many broadband applications and services, still it may not be able to meet the rapid increase of the traffic demands [3]. In particular, the holographic communication may require a data rate up to terabits per second (Tb/s), that is almost three times higher than the 5G's data rate and massive low latency (hundreds of microseconds), which is three time less than 5G's latency [4 – 6]. Moreover, because of the ever-increasing growth of the deployment of Internet of Things (IoT) and future Internet of Everything (IoE) devices, it would be necessary to improve further the connection density and coverage of 5G enabled IoT networks [7 – 8]. In addition, the future mobile networks are expected to be ultra-large-scale, highly dynamic, and incredibly complex system. Therefore, the manual optimization and configuration tasks used in the existing mobile networks would be no longer suitable for the next generation mobile networks [9 – 12]. At last, the new emerging services of Internet of Everything (IoE) such as extended reality (XR), telemedicine systems, mind-machine interface (MMI), and autonomous cars would demand high transmission rates, high reliability, and low latency, which significantly exceeds the original goals of the 5G networks [13 – 15].

Therefore, after the global deployment as well as global commercialization of 5G mobile network, the 6G network research initiatives have gained significant attention in both academy and industry.

The main goal of 6G network is communication at any time, and at any place with delay of 1 microsecond, and high data rate speed, by using higher-bandwidth frequencies over the longer distances than 5G network, such as THz waves, and artificial intelligence (AI). Due to the proliferation of IoT devices, the next generation of communication systems must meet stringent requirements for spectrum and energy economy, low latency and high throughput. These IoT devices would pave the way for novel services like telemedicine, virtual reality (VR) and extended reality (XR), environment-tal telemetry and condition tracking, autonomous cars, and linked drones and robots capable of transmitting full]HD video.

Artificial intelligence (AI) will be the main driving force in designing and optimizing 6G architectures, protocols, and operations. These networks would drastically re-shape the wireless evolution from "connected things" to "connected intelligence" [16]. 6G would provide support of ubiquitous and mobiquitous AI services from the core to the end devices of the network, which would exceed the mobile internet used today.

Now the initiatives of 6G primarily focus on identifying the main drivers, performance requirements, and technological innovations related to 6G.

In this direction, this paper highlights the vision of the technologies used in 6G network, 6G network scenario, 6G network challenges and potential solutions. The main contribution of this paper is the proposal of a 6G Advanced Wireless Mobile Heterogeneous Access Network (6G AWN-HAN) Architecture with artificial intelligence, whose description is expected to define the standard of 6G network.

Furthermore, it evaluates the performance quality of artificially intelligently, orchestrated services in 6G mobile networks in terms of energy efficiency. For this purpose it is used an analytical model where energy efficiency is expressed as the amount of user data rate transmission per user power consumption. The user data rate transmission, i.e., user throughput represents the quantity of data that can pass from source to destination in a specific time. In the simplest way it can be equal to the peak data rate equally shared by the users. For simplicity the user power consumption is expressed as a linear function of the user throughput. The research results show a significant improvement in energy efficiency by applying artificial intelligence at the edge of the network.

The rest of the paper is organized as follows. Section 2 explains the roadmap of 6G network. Section 3 provides details about 6G network requirements. Advanced AI 6G network model is evaluated in Section 4. Section 5 proposes 6G network architecture. Section 6 provides details of energy efficiency in 6G network and section 7 concludes the paper, addresses the challenges in 6G network that need to be resolved and provides directions for future work.

2. THE ROADMAP TO 6G NETWORK

Different standard organizations and bodies have proposed different roadmaps of 6G network [16]. The roadmap of 6G network envisioned by different organization standards, such as 3GPP, ITU, and PoC, is presented in Figure 1.

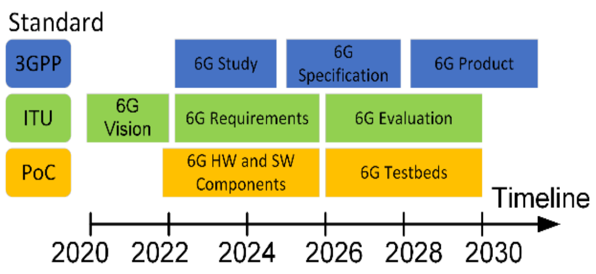

Fig. 1. The roadmap of 6G network

The phase about the vision of 6G network is already completed at the beginning of 2022. The next phase that includes study and definition of the 6G network requirements, as well as development of 6G network components has started in 2022. The definition of specification and standards of 6G network are expected to start around 2025. The evaluation and the testbeds of 6G network are expected to begin in 2026. The first 6G commercially deployed network would be after 2030.

3. 6G NETWORK REQUIREMENTS

6G mobile and wireless networks is expected to provide large coverage that allows subscribers to communicate with one another everywhere with a high data rate speed. To address the challenges and the issues that 5G network currently faces, it is necessary 6G network to be developed, innovative operations in shared spectrum bands among the network operators to be implemented, cooperation strategies in heterogeneous networks, and leasing networking slices on-demand to be used. In addition, 6G network would require higher frequency bands in the terahertz spectrum, quite large and opportunistic data rate to support demanding multimedia applications [17]. The end-to-end delay in 6G network should be less than 1 millisecond (about 1 µs), in order augmented reality, telepresence, and other delay sensitive services to be supported. Furthermore, 6G network should provide improved reliability comparing to 5G, in order mission and safety-critical applications to be enabled.

A comparison between 5G and 6G network parameters and requirements is given in [18, 19]. All parameters such as traffic capacity, data rate, end-to-end delay, processing delay, spectral and energy efficiency, etc. are expected to be improved several times over the value provided by 5G. A comparison between 5G and of 6G parameters are given in Table 1.

Table 1

A comparison of KPI requirements between 5G and 6G network

Parameter requirement	5G	6G
End-to-end delay	1 ms	1 µs
Traffic capacity	10 Mbit/s/m^2	10 Gbit/s/m^3
Latency	Fair	Slightly annoying
Localization precision	10 cm on 2D space	1 cm on 3D space
User experience	50 Mbit/s everywhere on 2D space	10 Gbit/s everywhere on 3D space
Downlink peak data rate	100 Gbit/s	1 Tbit/s
Uplink peak data rate	50 Gbit/s	~ 1 Tbit/s
Frame error rate (FER) reliability	10–5	10–9
Spectral and energy efficiency compared to today's network	10 up to 100 times in bits/s/Hz/m2/J	1000 times in bits/s/Hz/m^3/J (volumetric)

6G network would provide new use cases, which cannot be completely supported by 5G [19]. Some of them are holographic telepresence, industrial automation (industry 4.0 transform), e-health, tactile internet, augmented, and virtual reality.

As a result, many 6G services would appear. Most of the 6G services would be a hybrid combination of several 5G services. The services in 6G network would require low latency, high reliability, high data rate, massive connectivity, and full mobility. Some of the possible 6G services are massive URLLC (mURLLC), enhanced mobile broadband URLLC (eURLLC), and massive eMBB (meMBB) [19].

4. ADVANCED AI NETWORK MODEL FOR 6G

6G network would not be able to provide the necessary complex services demanded by the users with the guaranteed QoS and QoE parameters only by involvement of the humans in performing the manual network configuration and optimization. This can be achieved only by support of artificial intelligence (AI), which will auto-reconfigure and auto-optimize the network quickly enough to maximize traffic routing in order spectral efficiency to meet the service requirements. AI represents the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic for humans, such as the ability to reason, discover meaning, generalize, or learn from past experience.

Therefore, AI is the most influential and recently proposed enabling technology for the 6G network [20]. The conventional approach is to place the AI in the 6G core in all TCP/IP layers. This would introduce descriptive, diagnostic, predictive and prescriptive AI data analytics that will analyze the collected historical data to get insights of the network status especially of the PHY, MAC, Network and Transport layer [20, 21].

However, if the AI is placed only in the core part of the network, 6G would not be able to deal with the future Internet services and applications. This is because the conventional AI core service orchestration approaches that have been applied are not adequate to deal with the forthcoming large-scale and dynamic services and applications, since they cannot effectively cope with reduced latency, high mobility, high scalability, and real-time execution.

Therefore, another promising computing paradigm that recently started to gain enormous interest is the edge intelligence (EI) or edge AI located at the edge of the network [22, 23]. Moreover, big data sources as an enabling technology for learning based solutions have recently represented a significant shift from the cloud data centers to the ever-increasing edge devices, e.g., smartphones and industrial IoT devices. It is evident that these edge devices would push the AI solutions to the edge of the network to exploit the edge big data sources' potential entirely. In other words, just like cloud computing is distributed to the edge of 5G network, the artificial intelligence would also be distributed to the edge of 6G network. Therefore, an improved QoS and QoE would be guaranteed to the end users in terms of delay, user throughput and energy efficiency.

Following this direction here is proposed a new Hybrid AI Services Orchestrator (HAISO) model, which would ensure resilience and trustworthiness of open, large scale, dynamic services. To our best knowledge we did not find a similar model to be proposed. The HAISO would be primarily responsible for the composition of service elements available in the edge AI environment, such as, data analytics and data processing into more complex AI services, which could be offered to the end users. For some of the services may include sensing the traffic crowd sensing or planning the trip. The execution of such services is performed through multiple different components and entities that are spread in a wide area. This would increase the complexity in terms of decision-making process, particularly in the allocation of 6G network resources to achieve the QoS/QoE levels desired by the users. In order the execution of the AI services to be coordinated, it is necessary the orchestration mechanisms to be synchronized and combined from different service elements. Like that the QoS/QoE levels of a particular service, such as low latency, high user throughput and improved energy efficiency.

The HAISO would operate in a loosely coupled mode, which would consist with several levels: Edge AI Service Orchestrator (EAISO), Regional Domain AI Service Orchestrator (RDAISO), and Federated AI Service Orchestrator (FAISO), as it is shown in Figure 2.

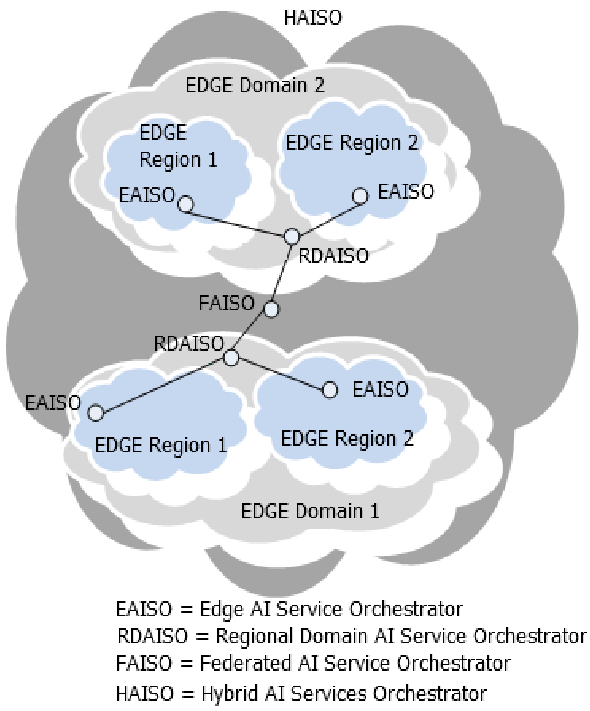

Fig. 2. Hybrid AI Services Orchestrator (HAISO) model for 6G network

The EAISOs are located at the edge of the network fog environment and enable semi-autonomous operation in different local edge regions. This allows the distribution of the load which provides scalability and much higher proximity to the end users with lower latencies.

The RDAISO is responsible for supervision of the EAISOs, within one edge domain. This level supports mechanisms that enable intra-domain cooperation between different local edge regions.

The FAISO is responsible for the management between different edge domains and allows a fruitful interaction among RDAISO modules. Such cooperation is enabled through various federation mechanisms implemented in FAISO module, which creates a multi-domain AI environment in 6G that should provide support of service ubiquity.

HAISO model provides flexibility and scalability, and it can be independently implemented in any network technology standard. It would possess its own federation machine learning mechanisms which would be implemented on all entities. In particular, the application of this model could be important for critical usage cases of IoT devices and Tactile Internet that requires 1 ms end-to-end latency to provide virtual-reality-type interfaces between humans and machines, and big data analytics that requires real time processing with stringent time requirement that can only be carried out in the fog.

5. 6G NETWORK ARCHITECTURE

An overview of the 6G network architecture that complies with the model described in the previous section together with the artificial intelligence is given on Figure 3.

AI data analytics is performed on the network which analyzes the collected historical data to get insights of the network status on the physical, medium access control (MAC), network and transport layer. It would provide network status and utilization opportunities. Work data which is obtained as an output of the network analytics processes would be used by Core data analytics for detecting and predicting the network anomalies to improve reliability and security of the network. The obtained data would be used to detect future faults based at historical and current information and network behavior.

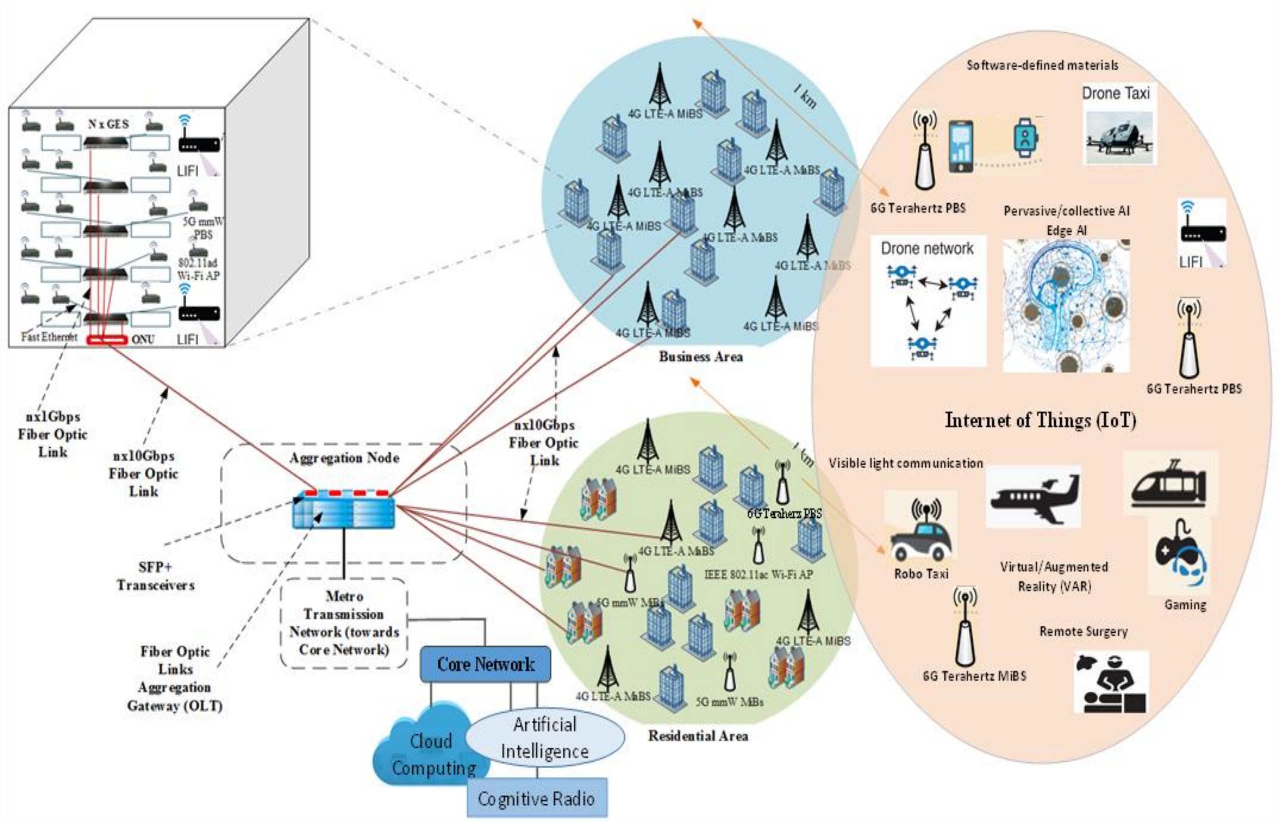

Fig. 3. 6G Advanced Wireless Mobile Heterogeneous Access Network (6G AWN-HAN) architecture with AI

Resource allocation solutions and notifications are expected to be output of this process. Predictive analytics would use data to forecast future resource availability based at user mobility prediction, traffic patterns and overload. It is expected optimized solutions to be proposed for allocation of the resources (open radio access network, i.e., ORAN and etc), network virtualization and slicing, edge computing, and optimization of virtual devices that consist of the network in order to offer ultimate network utilization, data transfer speed and traffic QoS. In some points core and predictive analytics may overlap. Even if this scenario looks naive it isn't, it must consider many parameters, i.e., big data deep learning mechanisms which need to be optimized if end-to-end traffic optimization is used.

In addition, there is an edge intelligence (EI) or edge AI located at the edge of the network. These edge devices would push the AI solutions to the edge of the network to exploit the edge big data sources' potential entirely.

6G networks would adopt ubiquitous AI solutions from the network core to the edge devices. However, the conventional centralized ML algorithms need the availability of a large amount of centralized data and training on a central server (e.g., cloud server or centralized machine). This would result with a bottleneck in the future ultra-large scale mobile networks [24]. Fortunately, federated learning (FL) which is an emerging distributed ML technique, is a promising solution to deal with this challenge and realize ubiquitous AI in the 6G networks. FL does not rely on storing all data to a central server where model training can occur. Instead, the innovative idea of FL is to train an ML model at each device (participant or data owner) where data is generated, or a data source has resided, and then let the participants send their individual models to a server (or aggregation server) and like that to achieve an agreement for a global model. However, despite the considerable potential advantages of FL for the 6G networks, FL is still in its infancy and encounter various challenges for fully operationalize in the 6G networks.

6. ENERGY EFFICIENCY IN 6G NETWORK

There are many ways to evaluate the quality of AI orchestrated services in 6G mobile networks. One of the most important QoS parameter is energy efficiency for the used bits per power consumption per user device, or vice versa.

The reduction of the power and power consumption by the networks and the devices is of vital importance for the economic and ecological sustainability in the industry. The general principle for minimizing of the power consumption at the network and the device should include all technology generations. This principle is recognized as an ecological goal and is quite important for the reduction of operating expenses in the network management [25]. In addition, the reduction of the power consumption would result to a longer battery life, which would contribute to a greater satisfaction of the mobile device users.

One of the possible methods to reduced power consumption in 6G mobile networks may be achieved by implementing the edge artificial intelligence.

The energy efficiency EE represents the amount of data that can be transfered through the power consumed per user, usually on a single cell, and represents the ratio between the user throughput R and the power P:

$$EE = \frac{R}{P}\left[\frac{\text{[bit/s/cell]}}{\text{[Joule/s/cell]}}\right] = \frac{R}{P}\left[\frac{\text{bit}}{\text{Joule}}\right]. \tag{1}$$

In the relation (1) R is the user throughput which represents the quantity of data that can pass from source to destination in a specific time. The user throughput of a particular smart device R for network can be calculated as a ratio between the peak data rate $R_{\max}$ of the network and the number of the user devices N, proportional to some weight coefficient μ:

$$R = \mu \cdot \frac{R_{\max}}{N}\,. \tag{2}$$

Here μ is a weight coefficient that models the bottleneck problem for the data that carry services from the AI computing data centers. The weight coefficient μ may receive any positive value between 0.7 and 1, and its value depends how much the AI data center is far away from the radio access network. If the AI data center is closer to the base station of the radio access network, then the coefficient μ has higher value close to 1, and if the cloud is at a greater distance from the base station of the radio access network, then the coefficient μ would have lower value. If the smart mobile device uses a service from edge AI networking intelligence, i.e., in the radio access network, then the weight coefficient μ is equal to 1.

In order to obtain the results of the user throughput the following values are used. The peak data rate of 6G network in downlink is set to be equal at 1 Tbps in both downlink and uplink direction [19]. The number of the users is varied from 100 to 1000. The weight coefficient μ is randomly taken to be 0.85 in downlink direction and 0.75 in uplink direction.

The consumed power P on the other hand, can be expressed through the user throughput R with the following linear [26 – 27]:

$$P = \alpha R + \beta \tag{3}$$

Here α is the coefficient that gives the power necessary for data transfer (in downlink, or uplink direction), β is a coefficient that represents the idle power [28]. According 6G requirements given in [19] the energy efficiency is about to increase by a factor of 1000, and therefore the typical values for the coefficient α is taken to be 10^{-6} W/Mbit, and the value for the coefficient β is taken to be 10^{-5} W.

Simulation results are presented at Figure 4 and Figure 5. It can be noticed that 6G offers much higher energy efficiency by using the edge AI, rather than the AI in the core part. This means that much higher quantity of data can pass through 6G network by using edge AI, for lower power consumption.

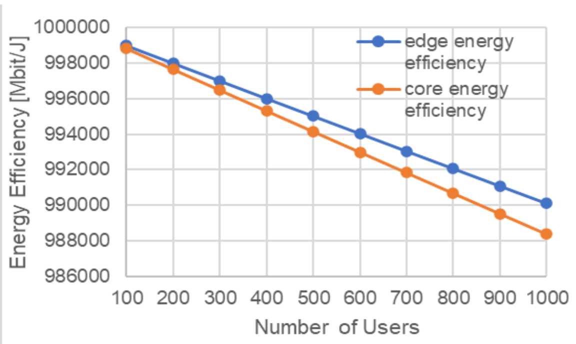

Fig. 4. A comparison of downlink energy efficiency in 6G network in both core and edge AI environment

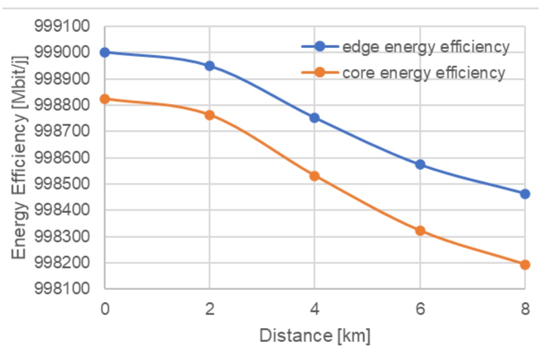

Fig. 5. A comparison of energy efficiency in 6G network in both core and edge AI environment, for 100 users

In addition, Figure 5 models the energy efficiency for 100 user devices, located at various distance from AI data center. Again, at every 2 km different modulation coding schemes, such as probabilistic constellation shaping, and QAM are applied. In other words, if the mobile device is closer to the AI data center than the energy efficiency is higher, because higher modulation coding scheme is applied, and therefore power consumption is lower and vice versa if the mobile device is getting more distant from the AI data center, then the energy efficiency is lowered because lower modulation coding scheme is being applied, and the power consumption is higher. Here again the energy efficiency is also higher if the service is being used by the edge AI, rather than the AI in the 6G core. Moreover in [29 – 31] it is stated that a basic goal of 6G communication is to operate battery-free whenever and wherever possible, with a target efficiency of 1 pico-joule per bit. And the simulation results given in Figures 4 and 5 nearly achieve this energy efficiency.

7. CONCLUSION

This paper proposed a 6G Advanced Wireless Mobile Heterogeneous Access Network (6G AWN-HAN) architecture with artificial intelligence, whose description is expected to define the standard of 6G network. Furthermore, it evaluated the performance quality of artificially intelligently, orchestrated services in 6G mobile networks in terms of energy efficiency.

The obtained research results show a significant improvement in energy efficiency by applying artificial intelligence at the edge of the network. In particular, the big data analytics that requires real time processing and very often has stringent time requirement can only be carried out in the edge AI.

This is essential for critical usage cases of IoT devices and Tactile Internet where 1 ms end-to-end latency is required in the network to provide virtual-reality-type interfaces between humans and machines (human-machine interaction and machine-machine interaction). 6G network would provide an improved intelligent human-to-machine type of communication of real-time controlling IoT devices [21]. The tactile internet would enable humans and machines to exchange control, touch, and sense data in a real-time manner, which would provide support for haptics interface, as well as, possible visual feedback and remote response behavior that would be used in the industry, e-commerce, and many other possible applications.

Another critical application in 6G network is the holographic telepresence, which would enable users to enrich their traditional audiovisual communication with the sense of touch, while they are in different geographical locations. Holographic telepresence has very strict requirements such as terabits data rate (up to 4 Tb/s), ultra-low latency (less than 1 ms), and reliable communications, which cannot be supported by 5G networks.

In addition, new augmented and virtual reality applications such as haptic technology and virtual meeting room (VMR) which would transmit a large amount of real-time data, and would require very low end-to-end latency, which can be accomplished by implementing edge AI intelligence in 6G.

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