Energy Efficiency with a low power consumption of 5G Networks by using Machine Learning.

A Thesis submitted in partial fulfillment of the requirements for the Degree of Bachelor of Science in Electrical and Electronic Engineering

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CERTIFICATION

This is to certify that this thesis entitled "**Energy Efficiency with a low power consumption of 5G Networks by using Machine Learning.**" is done by the following students under my direct supervision and this work has been carried out by them in the laboratories of the Department of Electrical and Electronic Engineering under the faculty of Engineering of Daffodil International University in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering. The presentation of the work was held on 05 February 2021.

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Dedicated to

MY PARENTS
And
TEACHERS
With Love & Respect

DECLARATION

We do hereby declare that this thesis is based on the result found by ourselves. The materials of work found by other researchers are mentioned by reference. This thesis is submitted to Daffodil International University for partial fulfillment of the requirement of the degree of B.Sc. in Electrical and Electronics Engineering. This thesis neither in whole nor in part has been previously submitted for any degree.

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LIST OF ABBREVIATIONS

2G - Second generation
3G - Third generation
4G - Fourth Generation
5G - Fifth generation
APC - Area power consumption
APRU - Average revenue per user
BS - Base station
CAPEX - Capital expenditures
CDF - Cumulative Distribution Function
DL - Down-link
DTX - Discontinuous transmission
E3F - Energy efficiency evaluation framework
EARTH - Energy Aware Radio and Network Technologies
FDD - Frequency Division Duplex
ISD - Inter-site distance
LTE - Long term evolution
MIMO - Multiple Input Multiple Output
NGMN - Next Generation Mobile Networks Alliance
OPEX - Operational expenditures
RB - Resource block
RF - Radio frequency
RX - Receiver
SNR - Signal to noise ratio
SINR - Signal to interference plus noise ratio
TDD - Time Division Duplex
TTI - Time transmission interval
TX - Transmitter
UL - Up-link

ABSTRACT

In an industry close to green power generation and minimizing power loss, power performance is more important than ever in the Wi-Fi community. Basic elements of community research and design. The 5G community is expected to offer a wide variety of products, including improved mobile broadband, word of mouth, highly reliable large equipment, and intermittent delays. A diverse community that uses many technological advances to provide a wide range of Wi-Fi products. The 5G network adopts a variety of technologies such as software defined networking, community function virtualization, third party computing, cloud computing, and small base stations to meet many needs. Therefore, the performance of electricity is the most important. To help achieve the mission of power productivity in the device community approach, you must be in a prime position and then win a huge fan in the studio community., Consider the Device Art utility. Master the 5G community strategy to power accessible, adjacent, and central communities. Based on the overview, we proposed the classification of plans to introduce 5G equipment to improve power productivity. We have discussed many of the challenges that device mastering can solve in terms of 5G power performance. Finally, we talk about many of the problems we want to solve. Use the full capabilities of the device domain to improve electrical performance in 5G networks. The survey provides a wide range of ideas related to the proliferation of 5G devices that will solve power performance issues in virtualization and help optimize, power distribution, and implement 5G technology. Decorate the power show.

CHAPTER-1

1.1 Introduction

Before the emergence of the fourth-generation cellular standard, the goal was to provide high data transmission rates. In recent years, technologies such as the Internet of Things (IoT) have produced billions of connected devices and generated huge amounts of data. The traffic is expected to increase exponentially, and it will increase by 1,000 times in 2020. In addition, the number of connected devices will continue to grow exponentially. It is estimated that there will be about 50 billion devices by 2021. As a result, the focus has shifted to other design requirements to provide various services, including:

• **Enhanced Mobile Broadband (eMBB**) -This use case is like the previous generation use case, and the goal is to provide faster data rates. The goal of 5G is 10 to 100 times higher than 4G and 4.5 networks, which is equivalent to 10 Gbps.

• **Ultra-reliable, low-latency communications (URRLC):** This purpose is for critical business services that require extremely low error rates (high reliability) and low latency. These applications usually do not require high data transfer rates.

• **Massive Machine Type Communications (mMTC)**: With the advancement of the Internet of Things, the ubiquity of devices has led to the need to develop connection standards that can support high device density with low power consumption. IoT devices are usually battery-powered and have a service life of several years (10 years).

Previous generations have not considered this situation. These requirements have led to the need to develop a communication infrastructure that can easily adapt to changes. In this sense, 5G networks are designed to provide general-purpose networks with high data rates, coverage, reliability, and low latency. Meeting these different requirements has also led to an increase in ICT energy consumption.

By 2025, the ICT industry itself may account for 30% of global energy consumption, and data centers alone will account for 3% of carbon dioxide emissions. In the cellular network, the base station consumes 80% of the total cellular energy, which is essential to improve energy efficiency. For example, many small cells are used to improve coverage and meet bandwidth requirements. Small cells make the network denser, leading to higher power consumption. According to the Small Base Station Forum, all small 4G base stations will be replaced by 5G small base stations in 2024, and 13.1 million will be installed by 2025. In addition, massive MIMO also increases power consumption because each base station requires more hardware components. Therefore, effective resource management and spectrum exchange are needed to improve energy efficiency.

Other factor that affects the power consumption of networked devices is power demand, which ranges from peak hours to low load times. Each time a new feature is added to the network, it consumes the most power. Such operations increase operating costs (OPEX) by adding special equipment. This can be solved by implementing infrastructure virtualization. It is not easy to manage network functions on dedicated devices, and a paradigm shift to traditional network management is required. Network function virtualization (NFV) can manage such mechanisms, eliminate the need for hardware and implement independent software functions. This virtualization not only provides flexibility, but also reduces operating and capital costs. Different virtual machines can share a common node to implement NFV functions. For example, in the case of RAN, virtual machines that provide baseband processing and other virtual machines for users on the core network. Politicians can use a knot. This method of reducing hardware implementation through virtualization can produce a more energy-efficient network. In addition, energy efficiency is directly affected by the data transmission rate; therefore, it is necessary to strike a balance between energy consumption and service quality. From the perspective of service providers, the decline in service quality is unacceptable. Therefore, the focus should be to maintain sufficient energy efficiency without compromising service quality. Due to capacity limitations and general network requirements, traditional methods are not sufficient to optimize the network. Machine learning techniques are used to enable the system to intelligently learn from data and optimize the overall performance of the network. For example, virtualization technology improves energy efficiency and resource utilization, and can save up to 50% of energy.

Machine learning can further improve energy-efficient virtualization and network optimization by sharing and consolidating loads. Intelligent resource allocation and management using machine learning techniques may also decrease energy usage at data centers, which consume most energy. Various machine learning methods may be used to increase 5G networks' energy efficiency. The model is trained on a series of data labelled to anticipate optimum solutions in supervised learning. A supervised app for learning is a large energy efficiency MIMO, which considers channel estimation and detection a challenge with a big number of antennas. Unlike supervised learning, unattended learning operates on unmarked input and is ideal for classification and reduction of dimensionality.

Unattended learning, for example, can be used to cluster BS with similar behavior in different load circumstances for energy-efficient operation. The application of enhanced learning techniques to energy-efficient solutions is appropriate if little or no preliminary data is needed for processing.

This study is intended to present a complete overview of current developments in access, edge and core network energy saving technology using machine learning. This article covered power assignment, resource optimization, pre-coding and other energy efficient approaches for 5G and energy efficiency

1.2. Motivation

In terms of bandwidth, throughput, latency and jitter the cellular technologies have progressively evolved from 1st Generation to 5th (5G). There were over 8.4 billion linked devices in 2017, including 2.7 billion smartphone users. Connected devices are anticipated to reach 20.4 billion by 2020, with 3.5 billion smartphone users. As smartphone users, wearables and IoT devices rise, it is challenging to provide high data speeds, coverage, and low latency. In addition, the addition of hardware to accommodate new applications and needs led to each generation's energy usage. 5G is likely to increase this typical energy usage trend significantly. The requirement to handle high data rates and a wide range of devices makes these networks energy hungry.

The energy usage is 4 times as high as 4G. 0.5 percent of the world's energy is being used by the mobile network. Ericsson according to the Mobility Report, in 2025, will boost user data four times compared to the current network. As a result, energy efficiency is an important aspect compared to 5G for generations before. To generations before. To achieve the broad range of services, several technologies are incorporated into the 5G network. These include the Software-Defined Network (SDN), Ultra-Dense Network (UDN), Network Virtualization Function, Cloud Computing. However, the integration of different technologies poses several energy efficiency difficulties. In the Ultra Dense Network (UDN) for example, even though energy consumption is reduced owing to low transmission power but the growth in computer requirements leads to increased power consumption in a dense scenario. This growth in computing power is expected to continue over time.

In addition, large MIMO technologies are utilized to service denser locations to meet rising demand. However, the balance between linearity and efficiency is important in large MIMO. The power amplifier measurements directly influence the energy efficiency of the large MIMO system. Linear production increases costs and non-linearity ultimately impacts energy efficiency. Appropriate hardware, efficient learning technologies (that can make intelligent energy-saving choices) and novel network architecture are needed to break over the energy curve.

Machine learning can address a few issues in 5G networks in this respect, thanks to the integration of numerous new technologies in an energy-efficient way. The aim behind this essay is to meet the rising demand for smart networks that decide to build energy efficient networks. Wireless communication and 5G networks in future generations are too varied to take judgments based on predefined and set criteria.

The capacity to interact with the environment and learn from the information provided enables the network to be designed to enhance the energy efficiency of the network. Furthermore, machine learning approaches can aid with many non-linear and non-convex challenges that may occur because of 5G deployment and network design in 5G or even future Wireless Networks.

Energy efficiency is also a major reason for worry for mobile network operators in terms of expenditure. Energy efficiency has ecological relevance in addition to economic value for network operators. SMARTer2020 issued a 2015 study indicating that carbon emissions will reach 1.27 GT by the end of 2020. (Around 2.3 percent of global emission)

1.3. LITERATURE EXISTING COMPARISON

Several 5G-technology studies have been done, energy efficiency assessments are either restricted to energy collection techniques, system design, virtualization, or architecture. Table 1 outlines some of the scientific contributions and limitations of the current energy efficiency review.

This poll, to the best of our knowledge, is unusual in that it catches the application machine from

another perspective. The categorization and review given in this work allows the scientist to comprehend with the end-to-end approach the relevance of various 5G machine learning approaches for energy efficiency.

1.4. CONTRIBUTION

The goal of this article is to give an exhaustive overview on energy efficiency in 5G networks facing problems such as mm Wave, CRAN, huge MIMOs, NFV, hetNets, tiny cells, and SDN utilizing machine learning. Few studies in their respective enabling technologies were done on energy efficiency in literature. None, however, classified the network by encompassing entire network requirements from the core to the access network. This survey includes different machine-learning energy-efficient approaches for researchers in the 5G network to benefit and further investigate. The key contributions are specifically emphasized as follows:

- A thorough discussion on the application of machine learning to improve energy efficiency, focusing on 5G technology capability.
- Review of 5G technology energy efficiency aspect utilizing the core network, access network and edge network method.
- Machine learning application taxonomy in 5G energy efficiency networks identified in the literature.
- Open concerns and future research guidelines to achieve 5G ecosystem energy efficiency.

CHAPTER-2

2.1. INTRODUCTION OF 5G, ENERGY EFFICIENCY, AND MACHINE LEARNING

This section provides a high-level review of 5G, energy efficiency, and machine learning, as well as the necessity for machine learning and its use in energy efficiency.

2.2. ENABLING TECHNOLOGIES AND 5G

The benefits of 5G include more coverage, lower latency, more capacity, and faster data speeds. The 3GPP has begun 5G research, which is expected to be completed by 2020, according to Rel 16. In comparison to 4G, 5G data rate standards are more stringen

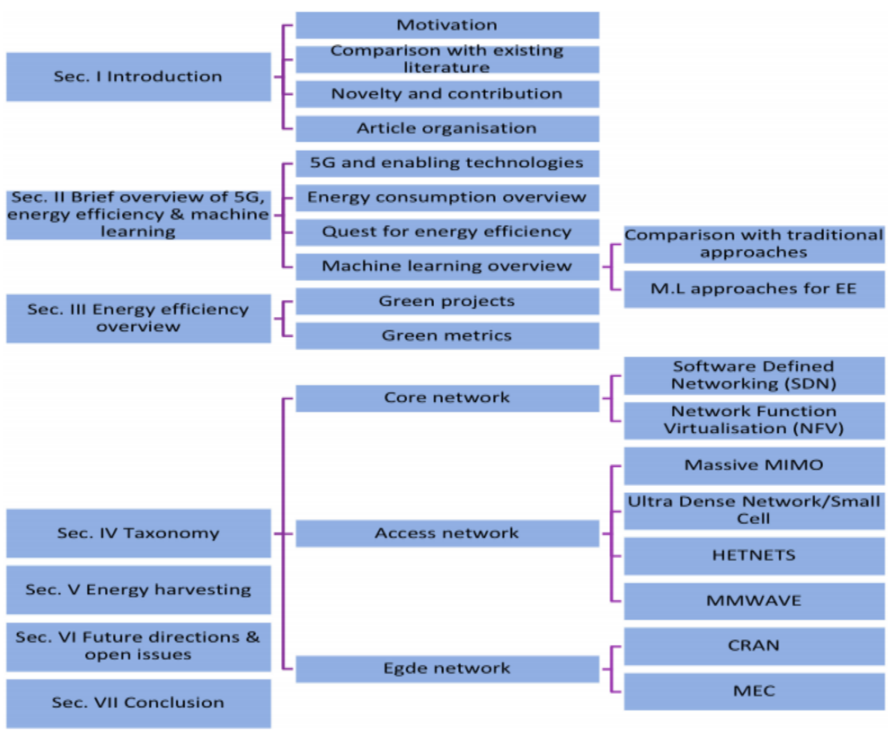

Figure 2.2. Paper Outline

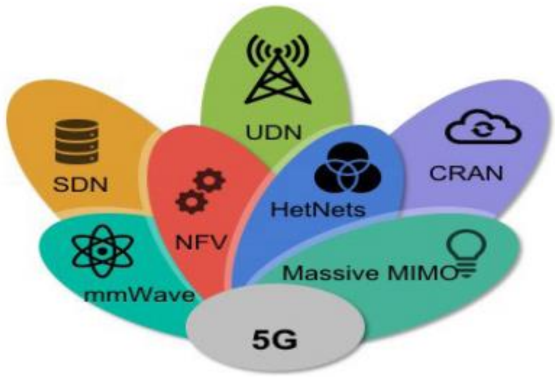

Fig-2.2.1: An overview of the technologies that were investigated for energy efficiency in this assessment.

are tenfold increased, necessitating a greater data rate and bandwidth. 5G intends to meet the needs of the new spectrum (C-band), which has greater frequencies. Bandwidth requirements Table 2 summarizes the performance differences between 4G and 5G, whereas Figure 2 depicts the 5G enabling technologies. Furthermore, with the introduction of VANET, IoT, and 5G-assisted smart healthcare, real-time data is now available.

The integration of the following enabling technologies is required for machine time management and high data rate:

- **Millimeter waves** range in frequency from 30 to 300 GHz.
  Users will have additional bandwidth as a result of this. A greater data transmission rate is associated with a larger bandwidth. At extremely high frequencies, however, attenuation rises, preventing mmWaves from being employed for long-distance communication. These high frequencies, on the other hand, operate well across short distances and are employed in tiny cells.
- **Massive MIMO** is a technology that connects several antennas to a single base station to increase spectrum utilization and data throughput. Due to effective beamforming and spatial multiplexing, it also results in less interference. Despite the benefits, several concerns, such as pilot contamination, channel correlation, and interference control, must be addressed.

- **Heterogeneous Network (HetNet)**, multiple radio technologies are deployed alongside legacy systems to offer seamless coverage and capacity. The most major barriers to energy efficiency are intertie and intrawire interference, resource allocation, and optimization.
- **Ultra-Dense Network** A dense deployment of tiny cells, known as an ultra-dense network, provides consumers with improved coverage and throughput.

Table-2.2: Performance difference between 4G and 5G (based on Verizon and 5G-ppp analysis).

Performance Criteria	**4G**	**5G**
Peak Speed	1.4 Gigabit/s	10 Gigabit
Latency	40-50 milliseconds	<10 milliseconds
Connectivity	10K-100K devices supported/mi^2	1 million devices supported/mi^2
Energy efficiency	90% more used energy/bit	90% less used energy/bit
Mobile data volume	1/100 Terabytes/s/Km^2	10 Terabytes/s/Km^2

- **Software Defined Networking (SDN)** By separating the data plane and control plane, Software Defined Networking (SDN) is one of the most important components for providing administration facilities to big and high-speed networks. SDN can coordinate and govern applications/services in a fine-grained and network-wide manner in a 5G network, resulting in more efficient network management.

- **Network Functions Virtualization (NFV)** breaks down functions (such as firewalls or encryption services) into connectable blocks and moves them to virtual switches, servers, or low-cost hardware. Network-specific hardware is costly and complex to program to adapt to changing network needs. Furthermore, the network's hardware has interoperability difficulties, limiting its flexibility. As a result, separating hardware from network operations allows for more scalability and flexibility.

- **CRAN (Cloud Radio Access Network)** is a widely recognized paradigm that provides characteristics such as central processing, energy-efficient infrastructure, real-time computing, and better spectrum use. Baseband Unit (BBU), Remote Radio Head (RRH), and Optical Transport Network (OTN) are the three components utilized to provide base-station functionalities, radiofrequency signaling, and their transmission to the cloud network. The use of densely deployed RRHs which are controlled by C-RAN enhances the scalability and improves network capacity.

- **MEC Mobile Edge Computing,** like CRAN technology, also aims to improve the RAN. CRAN focus on centralization and cloud services. In contrast, MEC aim towards decentralization by pushing the computation, processing, and storage close to the user. MEC decreases the latency and reduces network congestion in the back-haul network. ETSI proposed the idea initially to resolve the network congestion issue by using the distributive computing approach. Certain features of MEC have been introduced in 4G as well.

2.3. OVERVIEW OF ENERGY USE

Cellular networks have progressed from completely analogue to digital technology, allowing for global communication. Each generation concentrated on increasing data rate and capacity. It was not until 3G that energy efficiency became a major factor. GSM uses an average of 1.08kW to 1.20kW over a 15-minute time, according to a research on 2G and 3G power usage. For the same 15-minute time, UMTS average power usage was between 0.19 and 0.22 kW.

Another study found that 5G power usage during peak hours ranges from 1200W to 1400W, which is 300 percent to 350 percent more than 4G. During peak and off-peak hours, electricity usage differs substantially. Researchers recommended that base station radios be put into sleep mode to alleviate this issue, since base stations and RF transceivers used most of the electricity consumed (76 percent of overall power usage). The base station switching approach is a cost-effective method of reducing energy consumption and increasing efficiency. The ON/OFF behavior of the base station is determined by traffic patterns that change over time and space. Since 2009, China Mobile has been utilizing the same BS ON/OFF method, which has resulted in a savings of around 36 million kWh. Researchers began working on this BS sleep method to improve its effectiveness. Because of the many underlying technologies and the network's heterogeneity, considering the 5G network for this approach becomes more difficult. Site architecture, their distribution for coverage, the power consumption of electronic gadgets, and cooling systems were among the other obstacles in the energy-efficient practices (24 percent of total power consumption). Table 3 shows an estimate of total energy use in ICT, data centers, carbon footprint, RBS, and core network.

2.4. ENERGY EFFICIENCY STRATEGY

The Information and Computer Technology (ICT) industry arose around 1990, prompting research into power usage. Electricity usage was mostly split between business and household use of wired and wireless devices in the early days of ICT. If the rise in ICT usage from 2010 to 2015 is considered, when comparing 2015 to 2015, the power usage of communication networks grew by about 31%, from 185TWh to 805TWh. The energy consumption of 5G is significantly lower than that of 3GPP and 4G, according to Ericsson. Many publications over the previous few decades have highlighted the ICT sector's energy shortage. According to, energy consumption is expected to rise by 21% by 2030. Ericsson's recent study focuses on environmental factors and communication's long-term sustainability, with the goal of making networks ten times more energy-efficient by 2017.

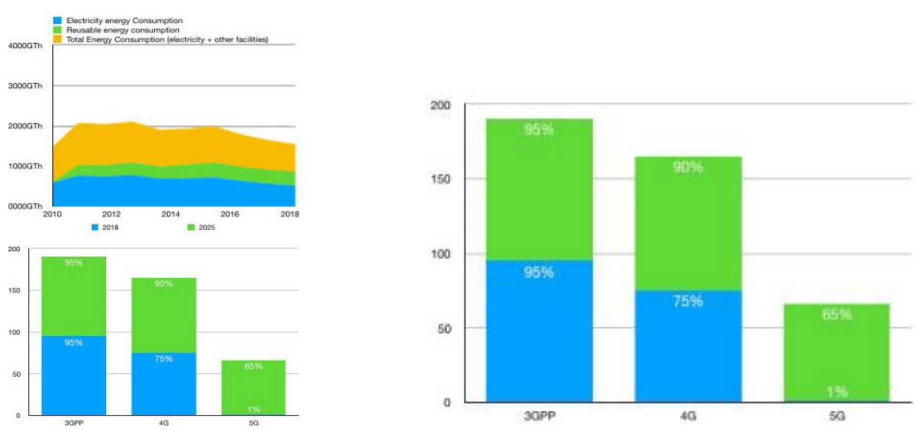

Figure- 2.4: Energy use of electricity, renewable energy, and electricity plus additional communication system facilities (a) Ericsson estimates for coverage of various technologies from 2010 to 2018 (b) Total energy consumption in 2018 and 2025

Energy efficiency was still in its infancy in 3G, and it was not a major focus of study. In comparison to 2G, the new modulation method, access mechanisms, and channel coding needed greater power. Because of its effective power regulation and resource use, energy efficiency improved with the introduction of CDMA. As a result, researchers began to investigate how electricity could be used more effectively in 3G data centers and base stations. Power reuse factors for 3G were described in, and they explored how to increase energy efficiency by reusing resources. For the best results, Dense low-power networks, renewable energy supply, power management, power reuse, and CDMA deployment were among the topics studied by energy-efficient network researchers. With the introduction of MIMO and OFDM in 4G, researchers sought to investigate both spectral efficiency and capacity. Energy issues were not taken into consideration at the time. MIMO was superseded by multi-user MIMO due to restrictions, which provides significantly better outcomes in terms of energy efficiency. OFDM is a multi-user diversity system that aims for spectrum efficiency as well as energy efficiency. According to, in the early stages of 4G, an efficient design was required to make network energy efficient. The author also discussed green energy standardization, metrics, and approaches that were required for 4G. In addition, ICT consumed roughly 4.7 percent of global energy consumption in 2011.

Base stations account for about 80% of the whole cellular network's energy consumption, with amplification and cooling accounting for 70% of that.

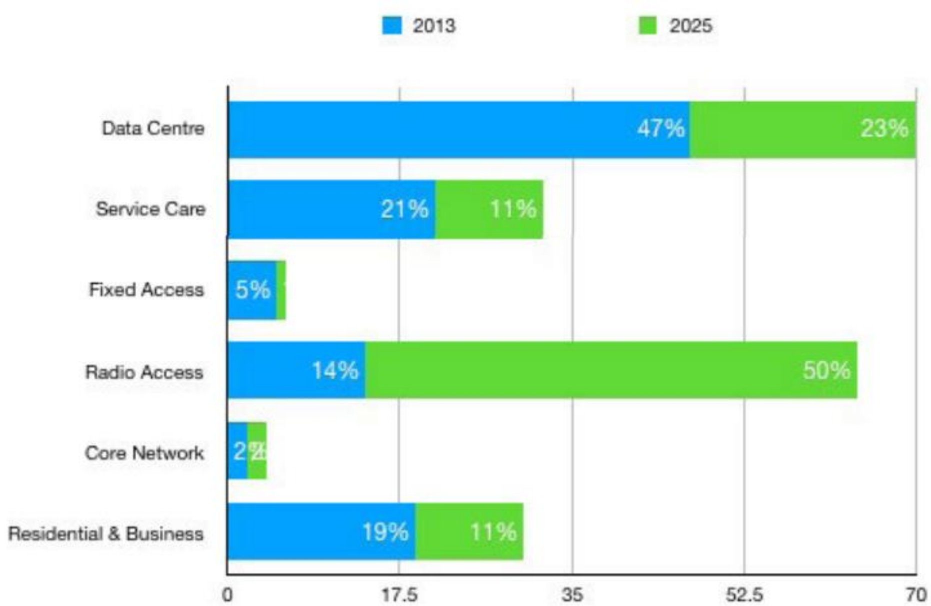

FIGURE- 2.4.1. Energy consumption estimation in communication system in 2013 and 20

CHAPTER-3

3.1. MACHINE LEARNING OVERVIEW

In the 1950s, engineers began to construct clever programs (artificial intelligence). Machine Learning (which does not require category programming) began to evolve in the mid-1980s and has since matured. Machine learning is a branch of Artificial Intelligence (A.I.) that is divided into three categories: supervised, unsupervised, and reinforcement learning. Deep Learning is a machine learning subfield that emerged in 2010 and is divided into three categories: supervised, unsupervised, and reinforced. Machine learning-based algorithms have recently been used to solve challenges in a variety of disciplines, including resource management and allocation [49], power allocation cell sleeping, and pre-coding. In this section, we'll take a look at the many machine learning algorithms that have been employed to create an energy-efficient wireless network. There is also a brief explanation of the advantages of using machine learning over traditional approaches for boosting energy efficiency in the 5G and beyond network.

3.2. TRADITIONAL APPROACHES ARE COMPARED

High data rates and a wide range of applications are required by the new wireless technology-based paradigm, which challenges old technology in learning and decision-making processes. The following are some of the M.L advantages over standard approaches:

- Learning speed improves dramatically, especially in large-scale issues, because machine learning can learn from its data, but older techniques are generally hard coded.
- Machine learning has independent decision-making capabilities, but traditional systems require a new set of instructions for each new function.
- Software development for new applications is a costly process.

Aside from the advantages, there are also disadvantages to machine learning when it comes to training. Machine learning integration for large-scale processing, security, and how research theories can be implemented at the application level.

3.3. MACHINE LEARNING APPROACHES FOR ENERGY EFFICIENCY

Supervised learning, reinforced learning, and unsupervised learning are the three types of machine learning. There is also a classification system for these strategies that can be used to solve specific difficulties. Table 4 summarizes the machine learning strategies described in this work. For channel-related problems including channel estimation, detection, and learning its behavior to make future predictions, supervised learning is the ideal solution. This is due to the fact that supervised learning generates output from acquired data based on previous experiences. Reinforced learning, such as resource allocation and management, is best for networks when the raised problems are unknown. Reinforced learning has the ability to alter its method in order to achieve the desired outcomes. It systematically learns from the findings and improves the decisions. Unsupervised learning differs from supervised learning in that it is more suited to wireless network clustering and spectrum sensing difficulties. It learns the network and solves the problem on its own, allowing it to solve more complicated problems than supervised learning. Machine learning categorization and learning algorithms are commonly employed in 5G enabling technologies and energy efficiency concerns, as shown in Figure

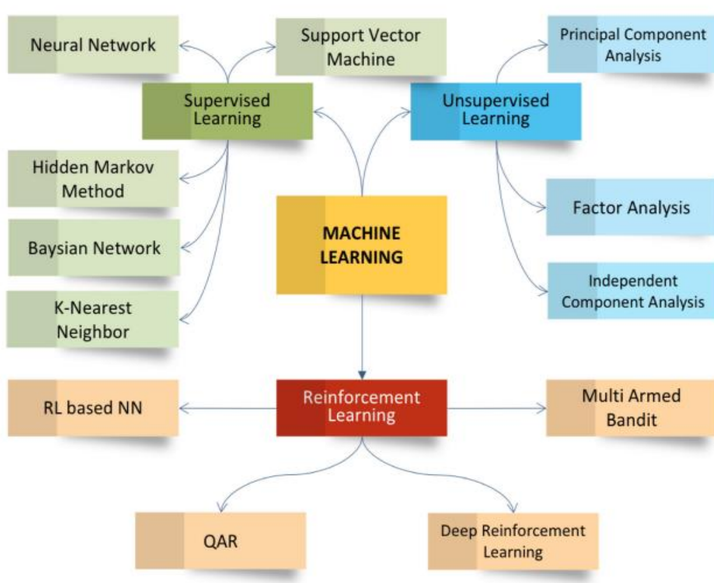

FIGURE- 3.3. M.L classification and techniques used for energy efficiency.

CHAPTER-4

4.1. ENERGY EFFICIENCY OVERVIEW

In terms of both economic and environmental problems, the objective of linking billions of gadgets is not viable. At the current rate of demand for network architecture, the network will consume 1000 times more energy than it does now. As a result of the energy shortage, researchers formed the Green Touch Consortium to study the crucial issue of green energy efficient networks. The major areas that can boost energy efficiency include resource allocation, network planning and implementation, energy collection and transfer, and hardware solutions.

The Shannon formula states that as bandwidth increases, so does the energy consumption factor. Massive MIMO appears to be a promising solution for dealing with spectrum and energy efficiency issues. To save energy, several antennas connected to a base station can go into sleep or turn off mode. The authors investigated the trade-off between spectral and energy efficiency in their paper. The suggested research used the benefits of the Rayleigh fading channel model for massive MIMO to allocate resources to boost energy efficiency. The authors of this study focused on both energy

efficiency and end-to-end delay. Aside from spectrum efficiency, increased bandwidth, small cell deployment, D2D/M2M communication, and ultra-dense networks, another interconnected concern that needs to be addressed is energy efficiency. 5G, on the other hand, has the potential to cut energy use by 90%. According to, energy efficiency is calculated as a ratio between a system's energy consumption and the number of Joules per bit capacity.

$$ECR = E_{sys}/C_{sys}$$

4.2. GREEN PROJECTS

The telecommunications industry is one of the most energy-intensive industries. When compared to overall ICT energy usage, data centers, base stations, and core networks have the biggest carbon footprint and energy consumption. It is estimated that by 2030, about 20% of worldwide CO2 emissions will have decreased. Despite all of the new IoT, architecture, and traffic growth, the main challenge is meeting the minimum energy consumption requirements. Researchers have been working on numerous projects to obtain dual benefits as a result of the demand for green communication. First and foremost, lowering energy costs, as this has a direct impact on profit projections. Second, lowering one's carbon footprint has an alarming environmental impact.

Many cooperative ventures and projects, such as those listed in Table 5, have been launched in recent years to reduce energy usage. It is mentioned in 5GrEEN, which took the initiative to emphasize the importance of energy efficiency in 5G. The Green Touch consortium set a goal in 2010 to reduce energy consumption by 90% by the year 2020. In 2006, the 5G Infrastructure Association, which covers the business side of the 5PPP, formed a 5G Infrastructure Evaluation Association Group. The goal was to create worldwide standards, collaborate on 5G standards for long-term testing, and deliver a more secure internet. Some of the other research efforts from previous years are included here.

Many more 5G initiatives for automobiles, vertical industries, and long-term 5G evolution are also in the works. In 2018, 5G-EVE, 5G-VINNI, and 5GENESIS began working on infrastructure enhancements in order to provide the groundwork for end-to-end 5G deployment. The projects 5G SMART, 5GROWTH, and 5G-SOLUTIONS were launched.

TABLE 4.2. M.L techniques discussed in this paper for energy efficiency

5G technology	Machine Learning technique
SDN	Unsupervised Learning Reinforced Learning Q-learning Neural Network
NFV	Supervised Learning Reinforced Neural Network Deep Learning Deep Reinforcement Learning
Massive MIMO	Deep Learning Machine Learning Deep Neural Network
UDN	Reinforced Learning Neural Network
HetNets	Deep Reinforcement Learning
mmWave	Deep Learning Deep Neural Network
CRAN	Machine Learning Deep Neural Network
MEC	Supervised Learning Deep Learning

Smart energy, machine-based remote operations, architecture, and dynamic network use will all be hot topics in 2019. The majority of these studies focused on the energy efficiency component of 5G, with a particular emphasis on load balancing. However, on-demand response modelling and service-level optimization, particularly on the power side, will need a significant amount of effort.

4.3. GREEN METRICS

Every five years, the network's volume increases by a factor of ten. Energy efficiency is now a critical component that must be considered in all aspects of development. Green metrics play an important role at all levels, from architecture to deployment, network to facility. If energy efficiency can be quantified, it appears to be understandable. They are used to calculate the amount of energy consumed and to compare performance trade-offs in order to improve efficiency. The following are the worldwide standardization bodies that are studying telecom equipment in order to improve global energy efficiency:

- The International Telecommunication Union (ITU) places a strong emphasis on energy efficiency, energy metrics, and environmental conservation and recycling. Their focus is also on the influence of greenhouse gas (GHG) emissions and how ICT can contribute to GHG emissions.
- The European Telecommunications Standards Institute (ETSI) is interested in the life cycle of telecom networks, telecom infrastructure, and ICT equipment, with a goal of reducing energy usage. Its key areas of focus are power optimization, energy consumption, power feeding, and the worldwide impact of ICT on energy. The Landscape of Climate Change Standardization
- The Alliance for Telecommunication Industry Solutions (ATIS) is a standard organization that offers ICT industry solutions that are constantly improving. It specifically addresses the energy and power consumption of telecommunications equipment at various load levels.

Green metrics can be used to measure and improve efficiency at the equipment, facility, and network levels. Energy Consumption Rating (ECR), Energy Efficiency Rate (EER), Access Per Cycle (APC), (ECG), (EEER) are some of the network-level metrics that are used to quantify energy efficiency at the network level, performance evaluation, and other elements linked to network capacity and coverage.

On a facility level, Power Usage Efficiency (PUE) and its subordinate metric Data Centre Efficiency (DCE) are applied for power. As equipment level measures, ATIS created the Telecommunication Equipment Energy Efficiency Rating (TEEER) and Telecommunication Energy Efficiency Ratio (TEER). Table 2 lists several additional energy measurements.

4.4. TAXONOMY

In the design and operation of 5G networks, energy efficiency has become increasingly important. The energy efficiency encompasses the entire network, including the radio access network, core network, and backbone network.

TABLE 4.3. List of green projects.

International Projects	Research	Year	Objectives	Conducted research	Ain of EE gain
Energy Neutral Sensor Networks (NEWSENs)	**Wireless Networks**	2019 to 2021	To design an architecture that works on renewable energy that works on RF technologies.	RF energy & wireless sensors	Renewable energy for wireless sensors
Innovative ultra-Broadband Wireless through transceivers (iBROW)	**Ultra-ubiquitous communications terahertz**	2015 to 2018	To develop energy efficient and low-cost wireless communication platform which capable to fulfil future requirements.	Platforms providing connectivity between fiber optics and highspeed wireless communication	Cost and energy efficient platforms development
Scalable and green wireless communications for a sustainable networked society (BESMART)		2017 to 2019	A wireless network that is self-sustainable, can share energy with other node for longer lifetime of network nodes and can configure itself by allocating efficient radio resource.	Distributed mobile networks	100% coverage in urban areas Reduction in energy cost Self configured network utilizing energy efficient resource allocation
MATILDA		2017 to 2019	To integrate 5G applications with demanding infrastructure and network functionalities	Smart Cities C-RAN virtual Resources	Up to 70% reduction in energy consumption
A Novel Radio Multiservice adaptive network architecture for 5G era (5G NORMA)		2015 to 2017	To develop a kind of network architecture that will cope the growing need of traffic because of heterogeneous networks.	For 5G flexible BS, controllers that are software based and can be centrally connected Software enabled RAN	To increase energy efficiency by selecting multi service efficient option.
Green Radio Project		3 years	To redesign backhaul, efficient resource allocation and multi-hop routing	Base station and handsets of mobile data services	Power efficient Dynamic spectrum access
Green Machine Learning for 5G and Beyond Resource Optimization		2021 to 2023	To develop green machine learning algorithms	Radio resource management	To lead the network towards intelligence and green communication

Mobile and wireless communications Enablers for the twenty-twenty Information Society (METIS) II		2015 to 2017	Radio access network designing	Technology components	Integrating technologies for efficient 5G framework
5G Infrastructure Public Private Partnership (5g PPP)		2015 on-wards	To evaluate IMT-2020 proposal	Network elements	To save up to 90% energy Advance privacy 1000 x more wireless area coverage
Green Touch		2010 to 2018	Improving EE 1000 times by 2020 by communication	Architecture and specification	It was assumed that energy factor will be cut down with a factor of 10 with 2010 baseline
ViruWind		2015 to 2018	For sustainable energy constraint	SDN NFV	Horizon 2020 & to use wind sector energy in cost reduction

TABLE 4.3.1. List of green metrics.

EE Metrics	**Level**	**Targets**	**Features**	**Unit**	**Pros & Cons**
Energy Consumption Rating (ECR)	Network level/Equipment level	Energy metric	A ratio is measured among maximum data throughput when the power is at peak	watts/Gbps	No network load consideration
Energy Consumption Rating-Variable Load (ECR- VL)	Network level/Equipment level	Energy metric	Dynamic power management	watt/bps	Works actively
Energy Efficiency Rate (EER)	Network level/Equipment level	Energy metric	Output data rate with respect to consumed power	bps/watt	Peciprocal of ECR
Telecommunica	Equipment level	Energy & Power	Calculates	x/watt (x	Includes

tion Energy Efficiency Ratio (TEER)		metric	energy and power efficiencies	depends on taken parameter)	environmental tests also
Telecommunications Equipment Energy Efficiency Rating (TEEER)	Equipment level	Energy metric	Tests variable load efficiencies	-log(Gbps/watt)	Not able to work on all properties of system
Normalized Power Consumption (NPC)	Equipment level	Power metric	Used for broadband wired access	mwatts/Mbps/km	Can connect multiple subscribers
Power Usage Efficiency (PUE)	Facility level	Power metric	Used to improve Watt operational efficiency of data centers	Watt	Works at marco level hence not able to assess individual level energy efficiency
Data Center infrastructure Efficiency (DCiE) & DCE	Facility level	Power metric	Inverse of PUE	Watt	Located within IT devices to calculate the total output
Energy Proportionality Index (EPI)	Equipment level	Network devices	Measurement is on the basis of consumed energy at idle mode and maximum load	Percentage	EPI= (Emax-Eint)/PM 100%
Key Performance Indicator of Energy (KPIEE)	Network level	Energy matric	Used for evaluation and testing	-	Significant practical approach
PI rural	Network level	Power metric	Evaluates rural areas network performance	km^2/Watt	Only for rural areas
PI urban	Network level	Power metric	Based on average busy hour traffic	users/Watt	For urban areas only

Data centers and technology are two things that come to mind while thinking about data centers. In this section, we'll go over the taxonomy of 5G enabling technologies and how they can be used to increase energy efficiency using machine learning approaches. Figure depicts the proposed taxonomy. There are other techniques, including resource allocation.

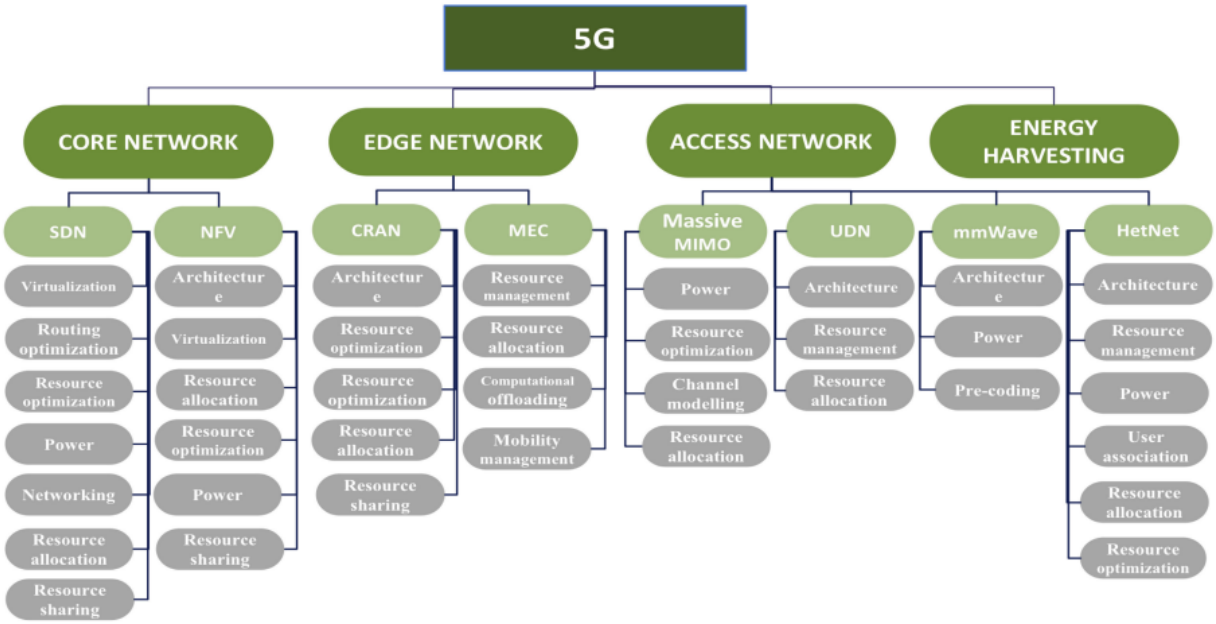

FIGURE-4.4. Taxonomy of machine learning application for energy efficiency in 5G.

To improve energy efficiency, management, resource sharing, bandwidth allocation, and power allocation have all been proposed. The next part provides a comprehensive review of energy efficiency in 5G and its solutions using machine learning.

CHAPTER-5

5.1. CORE NETWORK

5.1.1. NETWORKING DEFINED BY SOFTWARE (SDN)

More durable and self-contained 5G networks are necessary. Software Defined Networking (SDN) is the foundation of the 5G infrastructure (SDN). It is feasible to control the network centralized and intelligently using software applications in this network design. All communication between applications and services may be handled from a single location, allowing for real-time dynamic adaptation. Many ICT businesses have implemented software-defined networking in their data centers and network equipment, including Yahoo, Google, Facebook, and Cisco.

By separating the data plane from the control plane, SDN improves user experience by allowing for faster data rates and lower latency. Network switches begin to function as forwarding devices because of this separation. The traffic is controlled by a logically centralized controller, which replaces routers, switches, and the traditional table forwarding format. These switches and controllers are linked together using well-defined interfaces that have been pre-programmed. Control via controller is implemented using these application programming interfaces (APIs). OpenFlow is a widely used API, with well-known controllers such as NOX, POX, Beacon, Maestro, MUL, RISE, OpenDayLight, and NOX-MT [20]. This also aids in the management of the forwarding plane and the provision of access to the rest of the heterogeneous network. Intelligent networking, resource virtualization, and session management are just a few of the primary benefits of SDN.

Aside from a few advantages, there are a few difficulties in SDN that need to be looked into more. One of the drawbacks is an increase in overhead due to frequent controller queries. A system based on low-cost load-balanced route management (L2RM) is proposed to monitor the weight of traffic in fat-tree DCN to alleviate the congestion problem.

Adaptive route modification (ARM) is triggered in the second phase dependent on load. To prevent overload, a dynamic polling mechanism is used to update statuses. The proposed ARM method works in two ways. To begin with, it assists switches in staying up to date and removing outdated data to avoid overloading the buffer. Second, it only wakes up when it is required, saving both money and energy. In terms of overloading, the proposed system performs well in terms of energy efficiency. Data centers consume around 10% to 20% of total energy and over-furnishing the data center with resources results in significant energy inefficiency. SDN is one way for reducing energy waste and maximizing power usage during peak hours, resulting in traffic consolidation. Cloud computing is based on a contract between cloud providers and enterprises to ensure the quality of services delivered to clients. There is a risk of service level agreement (SLA) violation due to overbooking. proposes a method for increasing energy efficiency based on the overbooking ratio, which is calculated using link information and the correlation between virtual machines. When an overloaded scenario occurs, the VM is moved to a different host to avoid a SLA breach. Making them intelligent enough to learn from their surroundings is one way to tackle these problems. SDN comes in handy when it comes to implementing smart solutions. Machine learning may be used in conjunction with SDN to solve a variety of problems related to optimization, organization, and network resource management. The latest processing technologies, such as TPU, can also handle machine learning's high computational demands. These specialized purpose processors, such as TPU and GPU, offer the processing power to incorporate machine learning algorithms and deliver results in milliseconds. The majority of SDN effort is focused on traffic, security, and routing. To the best of our knowledge, combining machine learning with SDN to increase energy efficiency will require a large amount of research.

In this paper, we look at how machine learning techniques are utilized in SDN to improve performance and save energy. The feature extraction strategy, which involves feature learning (which helps discern various features from raw data) and feature reduction, is used in machine learning to extract the most related data. The output is determined by the characteristics chosen; more complicated features necessitate more extensive training.

More training equals more computational and memory power.

In any SDN, switches, ports, and active links require a lot of electricity. Minimizing the power factor of these switches and linkages is one approach to save energy. Furthermore, adjusting the flow pathways to achieve maximum throughput and least delay results in desirable network performance. To configure and control the network, the controller must have all of the latest network information. SDN can alter topologies based on this information. proposes an energy-efficient routing-based hybrid approach. Hymers, a supervised and reinforcement learning framework focusing on energy efficiency and routing, is explored. supervised learning is used in the initial stage for feature reduction using PCA, training, and testing. In the second phase, RL is used for network status components and links utility for dynamic routing based on repeated steps to the destination, whereas Q-learning is used for network status components and links utility for dynamic routing based on repeated steps to the destination. The proposed method is energy-efficient while also maintaining network performance. This method, however, necessitates substantial training with historical data. The output may be skewed if the training data is insufficient.

Combining SDN with machine learning is another method for maximizing energy efficiency. For traffic information and topology extraction, it is implemented on the POX controller. The feature size is reduced using principal component analysis (PCA). The data with reduced features, as well as topology, are fed into the model to train it. The proposed framework is made up of three modules: a traffic manager that stores data on traffic flow and topology status, and a topology manager that monitors topologies. Machine learning creates graphs for traffic demand based on past data. To train data sets, linear regression is used to create a regression model. The routing efficiency in SDN decreases due to the iterative update of OpenFlow.

The goal of routing techniques is to reduce energy consumption, particularly by reducing packet delivery time.

Energy efficiency and routing strategies are inextricably related. Using a neural network, a routing method was created that allows the controller to be centralized to the data flow. The data flow path can also be predicted using this technique, which aids in meeting QoS requirements. Data collection, neural network packet formation, training, routing, data processing, and rerouting are all controlled by a central controller.

Switches also help with flow forwarding, NN generation, and route prediction in the data plane. The control plane keeps track of network and topology discovery as well. When a packet is received, the switch analyses it before forwarding it based on the received request. Based on the received NN data, hop is predicted. The headers of packets are altered in accordance with each hop. A reroute request is generated in the event of a breakdown or an overloaded network.

The controller uses collected data to train the neural network for intelligent routing. One of the advantages of machine learning is that it is data-driven. As previously stated, the SDN controller provides global network awareness, which is useful for collecting data for machine learning. Not only that, but the configuration can be done in real time thanks to machine learning.

Because of its inherent characteristics, SDN has been used in transport networks, wireless sensor networks, network function virtualization (NFV), cloud radio access networks (C-RAN), the Internet of Things (IoT), and edge computing. Granularity, security, centralized control, lower operation costs, software-based traffic scanning, cloud level abstraction, and assured QoS are some of the other advantages of SDN.

5.1.2. VIRTUALIZATION OF NETWORK FUNCTION (NFV)

Independent service-related operations are at the heart of next-generation wireless networks. As a result, virtualizing network services is a method of reducing hardware consumption. By eliminating the traditional purposed hardware, installation, and up-grading for new services, Network Functions Virtualization (NFV) relieves network operators from escalating OPEX costs. In terms of energy efficiency, NFV has the upper hand.

With its integration into 5G architecture, about 30% of energy usage may be reduced. Network operators profit from NFV in a variety of ways, including:

- There is no location dependency
- It is assumed that there will be no energy usage while BBU is in the idle condition in an absolute state because there is no requirement for dedicated hardware.
- Improved operational efficiency and cost savings
- Reliable and seamless interoperability with cutting-edge technology
- Powerful and real-time virtualization

Because of the shorter pathways, the short distance between the user and virtual computers can also conserve power. NFV adoption is being aided by a number of standardization activities. ISG NFV of the ETSI community is in the release 4 phase, working on NFV evolution, automation, management, and orchestration [96]. Other standards bodies, including as the ONF, IRTF, IETF, OPNFV, ATIS, BBF, OVF, and 3GPP, are also involved in NFV standardization.

Virtual functions are distinct from logical systems in that they are placed virtually on commodity hardware. These are similar to the blocks that can be utilized in a variety of ways. Security, load balancing, and other EPC activities are provided by virtual network functions (VNF), which are virtualized operations implemented by the NFV platform.

NFV typically operates in high-performance modes that make the most of the CPU, most notably the Dynamic Voltage and Frequency Scaling (DVFS) mode, which aids in energy conservation. The energy usage of NFV is comparable to that of a dedicated CPU in high processing mode. In virtual settings, where physical machines are utilized for virtual network functions (VNF), deployment requires careful consideration to avoid excessive power consumption and inefficient resource usage. Furthermore, traffic processing is never the same throughout peak and off-peak hours, resulting in energy waste. Idle servers utilize the same amount of energy as active servers, but they waste more than half of it due to inactivity. Handling VNFs using machine learning is an excellent technique to reduce energy consumption, especially during peak traffic hours. The influence of active users in the network was explored using an energy-efficient NFV-based architecture on 5G. The goal was to look at energy consumption. As the core network virtual machine, all mobile core entities (mobility management entity, serving gateway, packet data network gateway, and policy & pricing rules function) are constructed in one virtual machine (CNVM).

The BBU is implemented in a virtual machine called BBUVM, and the RRH and BBU are decoupled. The traffic can only be passed through CNVM and BBUVM. The architecture provides services across flexible administration with an emphasis on energy consumption. The proposed method might save up to 38% of spent energy, according to the findings.

NFV Management and Orchestration systems (MANO) are used to manage virtualized infrastructure, communication, and network infrastructure, NFV entities, and their life cycles to handle complex networks. As previously stated, ETSI projects are in phase IV; nevertheless, the MANO framework can help with NFV management and orchestration. Open-source MANO for resource orchestrator, open baton for service orchestration, Juju for VNFM, open stack tracker for optimization and resource allocation, and X-MANO for sensitive information are the most relevant initiatives. Many services may be implemented via the network with the help of SDN, which provides flexible VNFs. Many virtual services, including as firewalls, servers, storage units, and load balancers, are classified as middleboxes in the traditional sense. All virtual functions should be interconnected to ensure optimal network flow. Service function chaining is the term for this type of connectivity that allows you to supply services all over the place (SFC). Multiple VNFs are supported by these SFCs to offer traffic flow and services. Aspects of service quality that must be addressed include proper resource utilization. As a result, resource assessment is an important part of a smooth service that should be utilised effectively. To make forecasts, a semi-supervised machine learning-based resource demand new model is proposed that uses NFV environment features. The LSTM model, which is a form of recurrent neural network (RNN), may employ both previous and current learning data. The data is further processed to remove ambiguities after training. After that, the SFC data is used to forecast performance. The results reveal that when compared to the simple LSTM technique, the proposed technique produces better outcomes. Deep Learning is offered as another resource allocation mechanism in NFV. It uses the timing characteristics to identify network traffic.

5.2. ACCESS NETWORK

5.2.1. MASSIVE MIMO

One of the crucial variables to consider for the next-generation network is bandwidth efficiency, which is one of several metrics to consider. Energy efficiency indicators have improved because of the rapid increase in carbon emissions and the increased power consumption of communication networks. MIMO became important because of its energy-saving capabilities and increased throughput. The notion of multiple base station deployment in massive MIMO is the same as TDD operations in conventional MIMO. It does not, however, necessitate additional power for transmission or bandwidth. MIMO (Multiple Input Multiple Output) is a well-known concept. It was set up in 4G mode, with one BS supporting eight antenna ports. Despite the fact that it is an old concept, it has not been fully implemented since conventional BS was deemed to be more cost-effective and MIMO to be more sophisticated.

Massive MIMO refers to the deployment of a high number of antennas when the MIMO concept enters 5G. Massive MIMO has several advantages over MIMO, including increased throughput, improved spectral efficiency, increased signal-to-noise ratio, increased capacity, reduced latency, increased data rate, and improved energy efficiency. Despite the benefits of huge MIMO as discussed, antenna location remains a problem in massive MIMO. To provide no-correlation among antennas, the basic guideline is to set an antenna with a spacing of half the signal wavelength.

Massive MIMO, which uses hundreds of channels on a single base station, improves spatial diversity. When a faded channel behaves like a non-fading channel, however, channel hardening occurs. In huge MIMO, random interference still exists, but it has little influence on communication. The wavelength can be reduced to obtain 0% correlation: the higher the frequencies, the lesser the likelihood of correlation.

The network becomes more spectrum efficient by transferring more bits per Hertz bandwidth. However, making the network more energy efficient is another challenge. With spatial modulation, this might be achieved. Massive MIMO outperforms MIMO in terms of bandwidth, energy efficiency, and spatial flexibility. The pilot contamination problem, on the other hand, is caused by inter-user interference when using the same reference signal. The cells are forced to use the same frequency blocks due to the frequency constraint. Pilot contamination is caused by orthogonal pilot sequences. Both standard BS and huge MIMO can suffer from pilot contamination. However, owing of the reuse of pilots, it drew more attention in the case of huge MIMO. Because the channel difference between conventional MIMO and massive MIMO is enormous, moving among different pilots (among big pilot sequences) reduces the risk of pilot contamination in any BS.

It's difficult to avoid pilot contamination in huge MIMO since there are more active terminals and more pilots are reused (pilots do channel estimate). Whereas with traditional MIMO, it can be overcome because the more terminals there are, the higher the pilot contamination. The two most utilized strategies to suppress pilot contamination are Regular Pilot (RP) and Superimposed Pilot (SP) [104]. In RP, data and pilot sequences are sent in pieces while the pilot sequence is adjusted. SP, on the other hand, is an old notion that combines data symbols and pilots instead of arranging them in time or frequency. In [105], the overlaid pilot was also promoted for real-time deployment via simulation. The proposed research claims that in hybrid systems, the overlaid pilot has produced better results.

Because of the increased array gain, uplink MIMO saves a large amount of power. Because of the coherent signal integration, this is achievable. The beams in the downlink, on the other hand, are targeted in a certain direction for users. Massive MIMO without the need of cells is a novel concept. To service many users, a large number of access points are deployed in a distributed fashion.

These access points (APs) operate on the same TDD and have one or more antennas. Because of the shorter distance between antennas, this approach provides high energy efficiency and spectrum efficiency even when serving many users at the same time-frequency. The cell-free massive MIMO idea is like small cell deployment; the main distinction is that multiple APs are deployed rather than a single AP. The energy efficiency factor of massive cell-free MIMO is determined by power allocation and consumption, channel estimate, and access point selection. Massive MIMO has progressed to the point where it now supports both multi-user and massive MIMO. Spectral efficiency, pilot contamination/decontamination, power allocation factor, and energy efficiency are all being studied.

For the system to learn from its user equipment location and allot downlink power, it employs a deep learning-based approach. TDD is explored for both user equipment and base station operations in a huge MIMO network.

The Monte Carlo approach is used to calculate the initial optimal powers, and the training is done offline. To allow the network to apportion power based on user location, a deep learning technique is deployed. It has been demonstrated that the maximum production method for neural networks outperforms traditional approaches in difficult calculations. When used jointly for power allocation, the max-min and maximum production approaches revealed incompetence, which was addressed with the LSTM layer of a separate neural network. Although the simulation yielded encouraging findings in terms of energy-efficient power allocation, the massive MIMO scenario investigated is insufficient to demonstrate its efficacy in a real-time situation. Deep learning, on the other hand, is a potential technique for solving real-time high computing problems since it can learn from the environment recursively.

Another work on pre-coding that has been presented incorporates deep neural networks because of their capacity to reduce computational complexity. During the training step, it makes use of structural data. Distributed massive MIMO is also regarded as an energy-efficient method of resource allocation.

Its throughput, energy economy, and channel modelling in a complicated environment are apparent when compared to conventional massive MIMO.

5.2.2. ULTRA DENSE NETWORK/DENSE SMALL CELL

Ultra-dense networks were necessary to meet the needs of densely populated areas that demanded more cell installations. The network's capacity can be increased in three ways: (a) by increasing spectrum efficiency, (b) by expanding bandwidth, and (c) by adding more cells.

The concept of dense deployment dates to 4G, when multiple cells were crammed into a small space. The cost element and interference among those microcells, on the other hand, surfaced, resulting in additional declining returns. Moving to cells that provide more coverage to end-users while requiring less deployment expense was a superior idea. Small cells (picocells, femtocells) provide coverage closer to end-users, utilize less power, and have about 90 percent more capacity than larger cells. Small cell deployment does not eliminate the need for microcells because the coverage area of small cells is insufficient in comparison to microcells, which is why microcells are still required to cover a broad region. The ultra-dense tiny cell network improves coverage while lowering power consumption and implementation costs.

Aside from coverage area, small cells must also consider frequency reuse. There are four types of small cells:

(a) Picocells are mostly used to boost capacity up to 100 meters and can be utilized both indoors and outdoors. (b) Femtocells are a form of small cell with similar properties to picocells, but with a coverage range of 10 as 30 meters. (c) Relays are the macro extension, and their indoor and outdoor deployment must be carefully planned to avoid interference. It has a somewhat broader coverage area than femtocells (up to 100m). (d) Because RRHs are generally connected to BS by a wired connection or microwave links, they can only be put outside with careful planning. The range of coverage is around 100 meters. Small cells require the same amount of electricity, around 100mW (inside) and 0.25W to 2W (outdoor).

Small cells deployed in a densely populated region do not solve all difficulties. There are also some additional difficulties, including as interference and increased energy use. For obstacles to be addressed, the integration of multiple methodologies is essential to resolve such concerns. Many other issues, such as interference, frequent handoffs, high energy use, and mobility, affect capacity. Because the goal of 5G is to employ higher frequency ranges, ultra-dense networks are seen as a viable alternative. It has the advantages of greater frequency use, dense deployment of small base cells (to meet growing traffic demands), and lower energy consumption.

As a result, the requirement for an energy-efficient network became unavoidable. In, a three-layer learning solution for dense small cell networks is presented, macro base stations and tiny base stations are deployed, and power grid feed energy is used for Macro Base stations (MBSs), and energy collecting techniques such as solar cells are employed for Small Base stations (SBSs). To save energy, SBS also features an on/off option. The suggested first layer makes decisions locally at SBS, maximizing resource use. The heuristically accelerated reinforcement learning approach is used. The second layer, which is built up of a multilayer feedback neural network and is also responsible for the energy component, makes decisions at MBS. This method yielded encouraging results in terms of radio resource management and energy efficiency for self-organizing networks.

5.2.3. HetNets

HetNets were first used in LTE-advance to improve spectral efficiency and capacity. The majority of macrocells were employed at the time for extensive coverage, while small cells were used to fill in the gaps. When compared to Pico, femto, and microcells, macrocells consume significantly more electricity. The network will require increased energy consumption, fast data speeds, and a huge coverage capacity with 5G. The key to greater user association and cell selection is dense deployment.

However, it has a few other drawbacks and obstacles, which will be examined further in this section. Even though small cells are more power-efficient than macrocells and the HetNet is the best option, there are certain challenges:

- As the number of macrocells and small cells grows, not only does the cost of installation rise, but so does the cost of operating towers and equipment.
- Interference between small cells and macrocells
- Coverage gaps
- A rise in OPEX

The architecture, number of nodes, and deployment of the network are the first factors that directly influence energy efficiency or power consumption. As previously stated, extensive deployment of tiny cells enhances coverage dramatically, but it also raises the cost of deployment and maintenance. Researchers were drawn to the pressing requirement for improved spectral efficiency in 5G as well as energy efficiency. The trade-off between spectral efficiency and energy efficiency is also covered in the spectral efficiency section. Multiple BS, focusing on HetNets deployment, are deployed, and they consume maximum power even when traffic is modest, resulting in OPEX and environmental energy efficiency problems. HetNets are made up of tiny and macrocells that are differentiated by power consumption but can be administered by the same person. In this case, resource management must use the same frequency to ensure that coverage is not compromised. To reduce interference, another option is to apply discontinuous bands to distinct cell types. The primary issue, after dense deployment and architecture solutions, is how users will be assigned to BS cells. User association, or the challenge of associating a user with a BS cell, has an impact on network performance. More accurate network information is necessary to handle the user association problem efficiently.

There is a need to solve the problem more efficiently and intelligently in a changing setting. Machine learning is an emerging technique that can help with this.

Uplink HetNets are used to handle the problem of energy efficiency, as well as user association optimization, employing deep reinforcement learning. Traditional problem-solving strategies are insufficient for such non-linear issues.

Deep reinforcement learning can solve real-time decision-making and resource allocation challenges.

Improved spectral efficiency and load across base stations, according to, are critical for avoiding congestion and improving user association. The choice to form a user association is completely based on the quality of service, demands and requirements, priority, and resource availability. Using the largest SINR for the association is one of the previously utilized user association approaches. However, when many users are linked to a single base station, performance suffers substantially. Several researchers used deep reinforcement learning (DRL) and deep neural networks to collaborate on user association and power distribution. DRL, according to [65], is an effective method for resolving complicated challenges. Another issue is re-association, which is just as critical as user association. User association gets more difficult with the addition of diverse cell sizes. User association is based on channel circumstances, bandwidth, base station load, and power usage. The available spectrum can be reused based on transmitter and receiver characteristics, making HetNets more spectrum efficient. HetNets become more energy efficient because of this reuse spectrum feature, which uses less power for both uplink and downlink.

The network's energy efficiency depends on efficient resource allocation. Complex non-linear problems like resource allocation, user association, and resource management can be solved with deep neural networks. The QoS for each femtocell and macrocell user is rewarded using a machine learning approach for resource allocation. As the environment changes dynamically, this helps to allocate power and get efficient energy more effectively. Another study on resource allocation employed a Convolutions Neural Network (CNN), which improved energy efficiency as well. The objective is to break down the resource allocation problem into classification and regression issues, resulting in low-complexity energy efficiency judgments.

When deployed in HetNets, small cells utilize the same spectrum as the microcell layer. The most power-hungry cells are macrocells. Small cell deployment can lead to spectrum reuse and lower energy use. Even with the spectrum reuse technique, interference is always present in small cells and microcells. The e-ICIC function helps to reduce this issue by allowing macrocells to reuse spectrums that are practically never used. As a result, tiny cell technology can assist the network in meeting the data needs of several connected devices as well as large data traffic. While tiny cells can deliver high data rates for communication, they also consume a lot of energy. It's critical to think about BS energy consumption and network advantages for operators, i.e., how to be profitable while using less energy.

5.2.4. mmWave

The majority of these operate at a microwave frequency of less than 6GHz. These frequency ranges are increasingly congested as the number of devices increases rapidly. Researchers are looking at novel ways to exploit unused frequencies, new spectrum, and alternative technologies. The utilization of a millimeter wave spectrum above 30GHz is one viable solution to this challenge. 30GHz to 300GHz is an underutilized frequency band in which 24GHz is used for microwave communications and is unlicensed, while 28GHz will be auctioned in 2019. In 2019, the Federal Communications Commission (FCC) encouraged the auction of high band mm Wave spectrum. The continuous spectrum for mm Wave communication will be 37GHz and 39GHz, totaling 2400 MHz, with an additional 1000 MHz for 47GHz. 2400MHz of 5G spectrum became available for auction in early 2020. However, most of the research has already been completed in the 28GHz, 71GHz to 76GHz, and 81GHz to 86GHz bands.

However, in recent years, academics have expressed concerns about its long-term viability. Its wavelength range is quite limited, which is why it is primarily utilized for line-of-sight communication and provides speedier data transfer.

Because of its wavelength, it is easily obstructed by any object. The following are some of the mm Wave limitations:

- mm Wave signals that deteriorate can have a negative impact on propagation.
- mm Wave offers high data rates but is also fragile (sensitive and easily affected by blockage). Because the size of rain droplets and mmWave wavelengths are nearly same, mmWave's sensitivity to weather, particularly rain, causes severe attenuation and impact communication. The main advantage of mmWave over previous wireless communication technologies is a ten-fold increase in data transmission frequency. Not only that, but additional antenna arrays may be put on transmitter and reception base stations due to the shorter wavelength.

Hybrid precoding has grown in importance as a field of study.

When paired with spatial multiplexing, it allows mmWave to benefit from beamforming. The energy efficiency of precoding systems is always significant. To rule out energy difficulties, architecture, planning, and hardware are also required. However, deploying energy-efficient hardware might result in high data rates. Hybrid coding is being researched by scientists (combining analogue & digital precoding). For mmWave hybrid precoding, channel estimate is required, and this is a tough issue. Millimeter waves' long-term viability, scattering, and sensitivity are all being questioned. Reflection and dispersion cause the channel to alter over time. It is difficult to estimate channel due to considerable computing requirements and complexity with massive antennas installed due to massive MIMO integration with mmWave (at transmitter and reception side).

Deep learning is thought to be a viable solution to such complex computational issues.

To improve precoding performance and spectral efficiency, a deep learning-based solution is proposed for hybrid precoding. For training purposes, a deep neural network-based framework is considered, which develops mapping linkages among several layers to initiate functions.

The system under consideration has a single base station and Uniform Linear Array (ULA) antennas, with no prior knowledge of the linkages. The system comprises of six hidden DNN layers for mapping, followed by training for mmWave statistical information. Because precoding techniques have a direct impact on energy efficiency, the deep learning strategy utilized for precoding can also be used to improve energy efficiency. Machine learning is used to suggest another energy-efficient hybrid coding solution for mm wave and massive MIMO. The hybrid precoder is created by adding their sum rates, which has a high likelihood.

When compared to standard approaches, this scheme demonstrated to be more energy-efficient and sum-rate hybrid precoding architecture.

Large arrays of antennas are commonly used in mmWave base stations to help overcome route loss, enhance spectral efficiency, and increase capacity. Energy efficiency becomes a challenge because of these huge antenna arrays. Analog beamforming is employed to maximize the energy efficiency of this installation. In the case of digital beamforming, however, spectral efficiency impacts will rise due to independent radio frequency chains.

The energy efficiency, on the other hand, will be diminished. In mmWave, both analogue and hybrid beamforming designs are used at radiofrequency and intermediate frequencies.

In, a deep learning-based beamforming solution focusing on baseband training and design difficulties is proposed.

Because there are fewer users than accessible RF chains in traditional mmWave communication, multiplex techniques (OMA, TDMA, OFDMA, and CDMA) are used. Traditional solutions are no longer sufficient as user capacity grows with 5G. Because it functions in the power domain, non-orthogonal multiple access (NOMA) is used. For high data rates, MmWave and NOMA deliver good performance. However, it necessitates an increase in energy usage. MmWave can give high bandwidth over a short distance, and MIMO allows for large-scale coverage. This combination has undergone a lot of development to use it for power control, pre-coding, and power allocation.

5.3. EDGE NETWORK

5.3.1. CRAN

End-users and the network are connected via radio links in a RAN. Architectural scarcity and end-user expectations are at the heart of every RAN innovation. BSS is the core of 2G and was standardized for GSM. It provides radio mobility services. The Digital Unit (DU) and the Radio Equipment Controller (REC) are the two devices that make up a typical BS. The DU handles all frequency functions like modulation/demodulation, frequency amplification, A/D and D/A conversion, and frequency filtration. At REC, baseband functions such as controlling and administering the base station are conducted.

As the number of end-users grew and GPRS evolved, a network architectural upgrade was required: GPRS BSS. GPRS emerged with packet-switching technology, whereas GSM used a circuit switching pattern. Both RAN systems may operate in simultaneously, however interface modifications and the addition of the Packet Control Unit were required (PCU). GERAN is the EDGE's access network and was created to meet the growing data needs of the GSM and EDGE networks. UTRAN was designed for UMTS and consists of several RNs, multiple transceivers, and a single controller (RNC). It differs from prior RAN architecture in that it focuses on higher data rates. UTRAN was terrain-dependent, with populations split into urban, rural, and suburban areas. E-UTRAN was created as a result of the LTE standardization, and it differs from all previous RAN systems in that it lacks a centralized controller. The X2-interface and the S1-interface are the two interfaces utilized in E-UTRAN. X2-interface handles all types of data transfer, mobility functions, load balancing, and interference cooperation. The S1 interface is further separated into two planes: the user plane and the control plane. The radio processing unit is separated from the signal processing unit in UTRAN, and the same is true in E-UTRAN. All frequency-related operations like as amplification (analogue to digital and digital to analogue), conversion and control, transport, and baseband functions were performed at the transceiver base station in the prior 2G RAN architecture. However, due to architectural changes and data requirements, performing all of these operations in one location proved impossible. D-RAN was born as a result of this. Remote Radio Unit (RRU) and Baseband Unit (BBU) were superseded by RRU and BBU, respectively, in DRAN. DRAN is the most efficient RAN architecture for 3G and 4G networks, according to.

Due to increased data demands, a new RAN design for huge data has been created, which also addresses the problem of interference. The user plane is now separated from the control plane in RAN design, and the SDN switch is used to interchange user data messages between the RAN controller and the other part from the control-based interface. This separation makes the RAN more adaptable to various NFV and SDN capabilities that are critical in 5G networks, such as MIMO, service chaining, and network slicing. Cloud/Centralized RAN refers to the concept of centralizing all data in one location; cloud and is seen as a less expensive OPEX and CAPEX (capital and operating costs) option. A generalized CRAN is made up of three primary components: I the RRH, (ii) the BBU pool, and (iii) a fronthaul network that connects them together. To optimize radio resources, the BBU pool has many software defined BBUs with centralized processors. RRH offers signal coverage and transfers RF signals from UE to BBU and BBU to UE through uplinks/downlinks. To be more specific, it amplifies radio frequencies, filters them, and converts them from analogue to digital and back. One of the reasons C-RAN is deemed energy efficient is because RRH is supplied in a cost-effective manner.

By providing advanced network design and support characteristics such as better performance, high capacity, expanded flexibility, energy efficiency, and reduced front-haul network cost, C-RAN delivers the edge to fulfil 5G technologies vision. As previously said, tiny cell technology is widely employed with CRAN to achieve the heterogeneous CRAN idea, which caters to high data rates and resource management. H-CRAN is a new idea that combines CRAN and heterogeneous to maximize resource allocation benefits. The main advantage of H-CRAN is that it takes advantage of the RRH benefits in terms of high data rate capacity, QoS, and energy efficiency. Low power nodes (micro-BS, macro-BS) consume more power than high power nodes (micro-BS, macro-BS) (Pico BS, Femto BS). The BBU pool houses all digital processing units. H-CRAN uses less energy because it can collect data. Because of its centralized architecture, the analytical process may be performed in real time. Interference is more severe when low-power nodes are deployed in a dense manner.

By eliminating interference, it is possible to reduce spectral efficiency degradation and energy usage. There are also more traditional methods for reducing energy use, such as turning off various BS that are not in use.

However, because of the close relationship between data services and convergence, they are not practical in every network. The primary determinant of energy efficiency is convergence.

The C-RAN development (centralization of baseband operations) eliminated most of the energy difficulties, allowing the network to install fewer BS.

However, further research is needed in the areas of resource usage and allocation, power in

C-RAN, and computational complexity. To increase energy efficiency and QoS interference for the H-CRAN downlink, a resource allocation approach based on machine learning is proposed. The suggested scheme learns information online and performs the allocation on the allocated controller. User traffic is prioritized and discriminated with location to be utilized as the initial learner to feed the machine, thanks to improved spectrum partitioning.

The allocation of power is based on a single controller connected to the BBU, which also requires network condition information to execute further energy-saving operations. Another machine learning-based resource allocation approach for downlink H-CRAN is proposed. The goal was also to save energy while maintaining service quality and reducing inter-tier interference. H-CRAN can accommodate many technologies and improve efficiency and resource allocation without requiring the transportation network to be rebuilt. In a wireless network, energy efficiency is a critical aspect that is directly tied to traffic demand and load. The radio resource index is another component that influences energy consumption, and the relationship between bandwidth and energy consumption is strong.

The cell sleeping concept is also employed to reduce power usage, as previously noted. Thus, simulation work has shown that enabling way, in combination with beamforming utilizing deep neural networks, considerably improves energy efficiency. CRAN has been targeted as a solution to the problem of joint cell sleeping. The optimization problem is solved using a deep neural network-based architecture. When the RRH is not being used for transmission, it is put into sleep mode so that the maximum amount of power can be saved. DNN can learn from its inputs and outputs to produce the best outcomes for time, accuracy, and energy efficiency in this suggested work. The significant decrease in power consumption is because of BBU placement in data centers, as the RRH has minimal power consumption. The work of the BBU is influenced by user traffic, data load, and demand.

As a result, managing BBU operations might lead to increased energy. For real-time scenarios, more time-efficient algorithms are required to solve the problem. Machine learning can be applied to the NP-hard problem (splitting DUs, diverse requirements nodes, and densely deployed high-power nodes) to minimize the computational time and power consumption.

5.3.2. MEC

Mobile Edge Computing (MEC) has emerged as a critical technology for 4G networks and can be easily implemented for 5G networks. It automatically combines network circumstances, location, and radio information to provide the best possible service to users. Consumers can choose the location of MEC installations in both 4G and 5G MEC. Because of the same deployment level, the transition between 4G MEC to 5G MEC is relatively simple due to the same resource usage, existing management methodologies, and easy control plane interaction. Integrating MEC with NFV and SDN, on the other hand, will improve its flexibility and offerings.

MEC's adaptability will eventually aid in obtaining URLLC by achieving the edge cloud milestone.

Despite the fact that contemporary mobile devices have high-speed processing units, they may not be capable of handling complicated processing. Furthermore, users are restricted from running computationally heavy applications due to battery usage constraints. As a result, Mobile Cloud Computing was created (MCC).

The end-user benefits from centralized clouds (CC) storage and computational resources in MCC. MCC has a centralized deployment yet has significant latency, jitter, and distance to user equipment, as well as plenty of storage and computing power.

MEC, on the other hand, is distributed and has low jitter, latency, and distance to user equipment, as well as limited storage and computational power.

Computational offloading is one of the many MEC advantages. Computational offloading provides a competitive advantage in terms of energy usage, response time, and performance.

In this article, three MEC use cases are discussed:

I Services geared toward consumers (ii) Network performance and QoE optimization services (iii) Operator and third-party services Because of the computational offloading, the consumer-oriented service use case benefits end users the most. MEC benefits low-latency applications like online gaming and some virtual and augmented reality. MEC is used as a gateway to deliver services in the second use case of operator and third-party services. The final use case is improving network performance. MEC can give real-time information, which helps to improve QoE and enable backhaul network and radio synchronization.

In order to improve energy efficiency, offloading options and resource allocation must be optimized.

It features cloud computing capabilities as well as location and radio data. Offloading decisions in MEC for energy consumption reduction were based on reliable channel status information, according to the proposed technique. However, precise channel state information is difficult to obtain for dynamic channels. Reinforced Learning (RL) can be used in these dynamic systems. To improve energy efficiency, an RL-based theme is applied. To fully exploit DRL features, certain states, rewards, and actions have been provided.

For multi-user equipment computational offloading, the proposed framework is applied. To optimize the service migration process, the Markov Decision Process (MDP) was applied. The service will be migrated according on the distance between the source and the UE. MEC differs from MCC in that it has fewer radio resources, storage, and computing resources. Offloading actions can be costly as a result of these constraints. As a result, adequate unloading is essential. Because of the various network conditions, a computational offloading framework is designed in order to reduce offloading costs. The recurrent offloading decision was made using a pre-calculated offloading solution. For MEC, Deep Reinforcement Learning is a great way to control complicated and high-dimensional issues. Furthermore, by examining deep connections for MEC, intelligent resource allocation and computational offloading may be determined.

CHAPTER-6

6.1. ENERGY HARVESTING

Algorithms and protocols are used to make wireless networks more energy efficient. Researchers are also investigating energy sources that are abundant in the environment. One technique to power network equipment is with renewable energy. The use of ambient energy from external sources is known as energy harvesting. Thermal, solar, wind, kinetic, radiation, and magnetic energy sources are all possibilities. The energy collected can then be stored or used directly in wireless devices. The following are some methods for harvesting energy for wireless communication:

• Using renewable energy sources Energy is harvested using natural resources such as solar, wind, and water. Because these natural resources are unpredictable, power variations occur.

• Techniques for coupling Inductive and magnetic coupling are the two coupling strategies utilized to harvest energy. For short ranges, both coupling approaches are used because they are reliant on distance and coupling coefficient.

• Power Transfer through Wireless (WPT) Radio frequency signals are employed to gather energy in the WTP. These electromagnetic waves are collected in the air to make use of energy that would otherwise be wasted.

Radio frequency energy harvesting addresses the aforementioned unpredictability of energy (from natural resources). Harvesting energy takes place in the radio-frequency band of 300GHz to 3kHz. Maintaining the energy flow and balancing fluctuations is critical for self-sustaining network architecture, as these can cause device damage and service disruption. Near-field energy generation is successful in 80% of cases, but over long distances, RF energy harvesting is employed, which necessitates the use of additional equipment such as antennas and rectifier circuits. Another method is to effectively use interference signals as energy harvesting, which has the advantage of not affecting system performance. The EH is best for portable devices that can't use the plugin power method, as well as those who need a lot of power.

In comparison to solar and wind energy harvesting resources, radiofrequency signals are considered a more efficient energy harvesting approach. Because of its reduced wavelength and cell shrinking capability, mmWave can engage a large number of antenna arrays in 5G communication. It's a good contender for energy harvesting in the future. The huge deployment of tiny cells to boost the capacity and energy efficiency of HetNets is driving the expanding 5G technologies. The energy harvesting concept can be used to improve the characteristics of small cells.

For small cells, a distributed Q-Learning technique is applied. Solar energy is used as a benchmark since it aids in the offloading of BS during the day. Each agent's decisions are made using the Markov decision process. Power is a constraint for machine-to-machine communication as the needs and challenges develop. Machine learning and energy harvesting techniques, along with cognitive radio, can outperform in terms of energy efficiency. Cognitive machine to machine (CM2M) devices need a lot of energy, and changing the battery is a pain. As a result, researchers began integrating energy harvesting with CM2M. This integration aids in the expansion of both spectrum and energy efficiency. EH-M2M uses cellular users' energy, but it can also harvest energy from the environment, which helps to extend device battery life. Other than power, machine-to-machine communication has issues such as network control, resource allocation, and scheduling. Spectrum reuse situations are used in a resource allocation technique introduced in to improve energy efficiency in EH-CM2M.

In, a new resource allocation strategy for EH-CM2M networks is described, which employs a deep reinforcement learning approach to improve energy efficiency. Shifting traffic to device-to-device communication is a possible solution to the M2M energy problem. D2D communication also allows users to converse with one another. Energy is captured from adjacent access points in the case of EH-D2D. The majority of D2D devices are data-hungry, which is why RF harvesting can help balance the need for additional energy. Many EHD2D academics have looked into resource allocation techniques in terms of power and resources. Energy harvesting for D2D communication is still in its early stages of development and will require major research resources.

CHAPTER-7

7.1. FUTURE DIRECTIONS AND OPEN ISSUES

Because 80 percent of wireless systems are made up of base station transceivers, radio interface components are the primary cause of energy efficiency. The simplest method to obtain green networks is to reduce energy use. 5G aims to improve spectral efficiency, provide ubiquitous coverage, and reduce latency. This can be accomplished by the modernization and reconstruction of network architecture (i.e. virtualization) as well as developments in radio access network technology (.i.e., massive MIMO). It will also improve system performance and reduce energy consumption. Although much research and testing has been done on network virtualization and softwarization, additional study is needed to address challenges like as hardware design and deployment, service chaining, energy efficiency, rules, and virtual functions. In this section, we'll go over some of the unresolved concerns and challenges.

1. Using many technologies: small cells work well in densely populated areas, but huge MIMO works well in sparsely populated areas. Depending on the density of the desired area, massive MIMO implementation differs. Because the 5G network is made up of a variety of technologies, merging them can result in a more energy-efficient 5G design. When compared to small cell networks, massive MIMO is less energy efficient. When the active antennas circuit consumes less power than switched off antennas, however, higher energy efficiency values are achieved. Because of its partially connected nature, Massive MIMO and mmWave can be coupled to provide a lower power consumption architecture. However, more research should be done on the architecture's dynamic installation. The ratio of computing power to transmission power determines the network's energy efficiency factor. These power values do not always remain constant due to the dynamic nature of the 5G network. As a result, in order to obtain overall network energy efficiency, the relationship between calculation power and transmission power should be investigated.

2. Real-time benefits: SDN controllers have the advantage of being able to program controllers aggressively. Because the central controller is not connected to the data plane, it can keep a real-time eye on the network and perform data configuration and monitoring. As a result, incorporating machine learning into SDN provides additional benefits to real-time networks. MEC is also a fantastic way to reap real-time benefits. MEC currently manages end-user mobility in the most basic of circumstances. In the future, however, managing several nodes while successfully controlling virtual machine migration will be a difficulty for ensuring service delivery.

3. Softwarization and virtualization: SDN and NFV can both be used in the same network. Regardless of their opposing personalities, they serve each other. In the form of connectivity across virtual network services, SDN can bring programmable benefits to NFV. NFV aids SDN by allowing network functions to be virtualized. Furthermore, there is much of room to investigate MEC's integration with SDN/NFV in order to meet rising user expectations and energy restrictions. In the future, research can be done on deploying content and applications on both the consumer and enterprise sides to minimise energy consumption and OPEX, as computational offloading improves energy efficiency.

4. Machine learning and data relationships: Considering the benefits of machine learning in solving complex problems to improve performance and ease of implementation, it is clear that it is a viable alternative to traditional algorithmic approaches. The ability of machine learning to learn from the environment is its greatest benefit. However, there is a serious paucity of research data sets available, and securing data from networks is problematic. The model must be trained even after the data has been collected. Prior to training, all data must be aligned, debugged, and cleaned of all skewed values, which will take a lot of time and effort. Future research should focus on the trade-off between efficient wireless network machine learning and model simplification. Particularly in locations where energy efficiency is a significant factor.

5. Reinforced learning in a real-world setting: Because of its weight assignment based on learning, reinforced learning is an excellent strategy to apply in real-time contexts. Another significant advantage of reinforcement learning is that it can function even when there is no sample or input/output data. It can learn from its surroundings in an iterative manner, including rewards and responses. However, it is not adaptive in a complex state space. This is due to the exponentially large storage space, which makes searching for data in the massive database challenging. More study is needed to overcome the problem of storing statistical data, as traditional inputs in the form of a vector make it difficult.

6. Collaboration & Exploration At the consumer end, MEC infrastructure is installed. Because of this user-side deployment, adequate communication between network providers is essential. This emphasizes the importance of a good protocol for network access collaboration despite varied deployment locations. For future MEC frameworks to reap low latency and energy efficient MEC benefits, a well-equipped discovery system is required to minimize wasteful calculations. Machine learning can also help with resource monitoring and synchronization on an ongoing basis.

7. Reliance on the front end the need for front-haul bandwidth is increasing as user data requirements increase. Because of the high cost of fronthaul deployment, not only will expanded infrastructure and increased OPEX and CAPEX be a challenge, but so will increased OPEX and CAPEX. It will also result in a reduction in energy efficiency. To address these concerns, fronthaul networks must have low latency and large capacity to address the existing capacity shortage.

8. Device-to-device communication: The energy efficiency of device-to-device communication is harmed by frequent device discovery activities. It is reliant on protocols that force devices to listen for and exchange discovery messages on a regular basis. In the future, more research will be needed to address the energy challenge posed by these frequent discovery issues.

Chapter-8

Conclusion

With the help of numerous enabling technologies, 5G is a varied network that will enable a variety of services. Virtualization, softwarization, novel RANs, and backhaul methods are the major drivers. All of the 5G enablers will assist give incredibly low latency, tremendous throughput, and huge connection all at the same time. Furthermore, network densification is required to meet growing network capacity, geographic coverage, and traffic needs. All of these enhancements to serve a variety of use cases will eventually result in higher energy consumption than previous generations. From both an environmental and a business standpoint, this is unsustainable. Because of both economic and environmental concerns, the necessity for an energy-efficient network is being accepted globally. Over the last few years, a lot of research has been done on improving energy efficiency in 5G networks. There has been an increasing interest in utilizing machine learning techniques to solve energy efficiency at various 5G network tiers due to autonomous decision-making skills and the benefit of learning from its environment.

We studied the state-of-the-art literature in order to address the energy efficiency issue in the 5G network as well as the necessity for intelligent learning in this article. We suggested a taxonomy for this purpose, dividing the 5G network into three basic parts: access, edge, and core. The usefulness of machine learning in improving energy efficiency is explored when discussing the enabling technologies within the provided taxonomy. Finally, machine learning has the potential to reduce energy consumption and increase performance in future networks, even in the face of changing network conditions. Machine learning can optimize the functioning of a 5G network while also boosting energy efficiency if properly deployed. However, to develop extremely energy-efficient networks, several key difficulties must be addressed. We did so by highlighting some of the most important issues that need to be thoroughly examined, as well as providing future study directions.

REFERENCE

[1] N. Panwar, S. Sharma, and A. K. Singh, ‘‘A survey on 5G: The next gen- eration of mobile communication,’’ *Phys. Commun.*, vol. 18, pp. 64–84, Mar. 2016.

[2] A. Fonseca, R. Kazman, and P. Lago, ‘‘A manifesto for energy-aware software,’’ *IEEE Softw.*, vol. 36, no. 6, pp. 79–82, Nov. 2019.

[3] P. Lahdekorpi, M. Hronec, P. Jolma, and J. Moilanen, ‘‘Energy efficiency of 5G mobile networks with base station sleep modes,’’ in *Proc. IEEE Conf. Standards for Commun. Netw. (CSCN)*, Sep. 2017, pp. 163–168.

[4] D. D. Johnson. (Oct. 2018). *The 5G Dilemma: More Base Stations, More Antennas-Less Energy?* [Online]. Available: https://spectrum.ieee.org/energywise/telecom/wireless/will-increased- energy-consumption-be-the-achilles-heel-of-5g-networks

[5] S. Rajoria, A. Trivedi, and W. W. Godfrey, ‘‘A comprehensive survey: Small cell meets massive MIMO,’’ *Phys. Commun.*, vol. 26, pp. 40–49, Feb. 2018.

[6] B. Yi, X. Wang, K. Li, S. K. Das, and M. Huang, ‘‘A comprehensive survey of network function virtualization,’’ *Comput. Netw.*, vol. 133, pp. 212–262, Mar. 2018.

[7] E. Björnson and E. G. Larsson, ‘‘How energy-efficient can a wireless communication system become?’’ in *Proc. 52nd Asilomar Conf. Signals, Syst., Comput.*, Oct. 2018, pp. 1252–1256.

[8] M. Zakarya and L. Gillam, ‘‘Energy efficient computing, clusters, grids and clouds: A taxonomy and survey,’’ *Sustain. Comput. Informat. Syst.*, vol. 14, pp. 13–33, Jun. 2017.

[9] R. Yadav, ‘‘Challenges and evolution of next generations wireless com- munication,’’ in *Proc. Int. MultiConf. Eng. Comput. Scientists*, vol. 2, 2017, pp. 619–623.

[10] J. Vidal, ‘‘Tsunami of data could consume one fifth of global electricity by 2025,’’ Climate Home News, 2017, vol. 11.

[11] C.-L. I, S. Han, and S. Bian, ‘‘Energy-efficient 5G for a greener future,’’ *Nature Electron.*, vol. 3, no. 4, pp. 182–184, Apr. 2020.

[12] M. A. Al-Namari, A. M. Mansoor, and M. Y. I. Idris, ‘‘A brief survey on 5G wireless mobile network,’’ *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 11, pp. 52–59, 2017.

[13] (Jun. 2020). *Ericsson Mobility Report*. [Online]. Available: https://www.ericsson.com/49da93/assets/local/mobility-report/documents/2020/june2020-ericsson-mobility-report.pdf

[14] K. Demestichas, E. Adamopoulou, and M. Choraś, ‘‘5G communi- cations: Energy efficiency,’’ *Mobile Inf. Syst.*, vol. 2017, Apr. 2017, Art. no. 5121302.

[15] (Jun. 2020). *Ericsson Mobility Report*. [Online]. Available: https://www.ericsson.com/en/mobility-report/reports/june-2020

[16] S. Zhang, X. Cai, W. Zhou, and Y. Wang, ‘‘Green 5G enabling technolo- gies: An overview,’’ *IET Commun.*, vol. 13, no. 2, pp. 135–143, Jan. 2019.

[17] M. Usama and M. Erol-Kantarci, ‘‘A survey on recent trends and open issues in energy efficiency of 5G,’’ *Sensors*, vol. 19, no. 14, p. 3126, Jul. 2019.

[18] S. Buzzi, C.-L. I, T. E. Klein, H. V. Poor, C. Yang, and A. Zappone, ‘‘A survey of energy-efficient techniques for 5G networks and chal- lenges ahead,’’ *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 697–709, Apr. 2016.

[19] I. B. Sofi and A. Gupta, ‘‘A survey on energy efficient 5G green network with a planned multi-tier architecture,’’ *J. Netw. Comput. Appl.*, vol. 118, pp. 1–28, Sep. 2018.

[20] Y. Jarraya, T. Madi, and M. Debbabi, ‘‘A survey and a layered taxonomy of software-defined networking,’’ *IEEE Commun. Surveys Tuts.*, vol. 16, no. 4, pp. 1955–1980, 4th Quart., 2014.

[21] S. Bera, S. Misra, and A. V. Vasilakos, ‘‘Software-defined networking for Internet of Things: A survey,’’ *IEEE Internet Things J.*, vol. 4, no. 6, pp. 1994–2008, Dec. 2017.

[22] F. Z. Morais, C. André da Costa, A. M. Alberti, C. B. Both, and R. da Rosa Righi, ‘‘When SDN meets C-RAN: A survey exploring multi- point coordination, interference, and performance,’’ *J. Netw. Comput. Appl.*, vol. 162, Jul. 2020, Art. no. 102655.

[23] R. Alvizu, G. Maier, N. Kukreja, A. Pattavina, R. Morro, A. Capello, and C. Cavazzoni, ‘‘Comprehensive survey on T-SDN: Software-defined net- working for transport networks,’’ *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2232–2283, 4th Quart., 2017.

[24] M. Kamel, W. Hamouda, and A. Youssef, ‘‘Ultra-dense networks: A survey,’’ *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2522–2545, 4th Quart., 2016.

[25] K. Zheng, L. Zhao, J. Mei, B. Shao, W. Xiang, and L. Hanzo, ‘‘Survey of large-scale mimo systems,’’ *IEEE Commun. Surveys Tuts.*, vol. 17, no. 3, pp. 1738–1760, 3rd Quart., 2015.

[26] A. Kassaw, D. Hailemariam, and A. M. Zoubir, ‘‘Review of energy effi- cient resource allocation techniques in massive mimo system,’’ in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, 2018, pp. 237–242.

[27] N. Sapountzis, T. Spyropoulos, N. Nikaein, and U. Salim, ‘‘User association in HetNets: Impact of traffic differentiation and backhaul limitations,’’ *IEEE/ACM Trans. Netw.*, vol. 25, no. 6, pp. 3396–3410, Dec. 2017.

[28] W. Z. Khan, E. Ahmed, S. Hakak, I. Yaqoob, and A. Ahmed, ‘‘Edge computing: A survey,’’ *Future Gener. Comput. Syst.*, vol. 97, pp. 219–235, Aug. 2019.

[29] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, ‘‘A sur- vey on mobile edge networks: Convergence of computing, caching and communications,’’ *IEEE Access*, vol. 5, pp. 6757–6779, 2017.

[30] N. Abbas, Y. Zhang, A. Taherkordi, and T. Skeie, ‘‘Mobile edge com- puting: A survey,’’ *IEEE Internet Things J.*, vol. 5, no. 1, pp. 450–465, Feb. 2018.