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**ENHANCING THE 5G NETWORK PERFORMANCE
BY CACHE-AIDED NON-ORTHOGONAL MULTIPLE
ACCESS (CA-NOMA)**

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Master's Thesis

Supervisor

Asst. Prof. Dr. Muhammad ILYAS

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The thesis titled ENHANCING THE 5G NETWORK PERFORMANCE BY CACHE-AIDED NON-ORTHOGONAL MULTIPLE ACCESS (CA-NOMA) prepared by ABDULLAH SAAD ZEKI ZEKI and submitted on 09/12/2022 has been **accepted unanimously** for the degree Master of Science in Electrical and Computer Engineering

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Abdullah Saad Zeki ZEKI

Signature

DEDICATION

I thank God Almighty for helping me and granting me success in completing this thesis.

This thesis is wholeheartedly devoted to the memory of my mother and father. It is impossible for me to put into words how much it means to me. There is absolutely nothing I can do to make up for what you have done to me. I shall keep doing everything in my power to live up to the standards you have set.

In conclusion, I would want to say thank you to my family. They helped me a lot and encouraged me to complete this project.

ABSTRACT

ENHANCING THE 5G NETWORK PERFORMANCE BY CACHE-AIDED NON-ORTHOGONAL MULTIPLE ACCESS (CA-NOMA)

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5G wireless systems aim to meet unprecedented technical challenges. Therefore, many devices require that data, voice, and various operations are processed through a 5G network to improve the quality of life. This explains the need for better hardware specifications, and as a result, we find that more industries are moving towards using the 5G wireless network. The 5G network has improved the response time. As well as improving the data transmission rate to maintain a reliable connection throughout its entire band with a data transfer rate of at least 1 gigabyte per This allows the inclusion of a huge number of devices, as it will allow them to pass a data rate of up to one hundred times the rate of the 4G network. One of the new technologies in the fifth-generation network is the (CA-NOMA) technology which depends on the code domain or the energy domain that greatly accelerates data transmission. Also, artificial intelligence has contributed greatly to the development of communication technology in the field of vehicle networks concerning autonomous driving. In this paper, we will work on improving the performance of the work of (CA-NOMA) in the power phase through neural networks and

we will focus on two types (MobileNetV2) (and NasNETmobile) and compare between them in terms of performance and integration.

Keywords: 5G, CA-NOMA, MobileNetV2, Convolutional Neural Network, NasNETmobile

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ABBREVIATIONS

AI	:	Artificial Intelligence
5G	:	Fifth generation
IoT	:	Internet of Things
MIMO	:	Multiple-Input Multiple-Output
NOMA	:	Non-Orthogonal Multiple Access
OMA	:	Orthogonal Multiple Access
OFDM	:	Orthogonal Frequency Division Multiplexing
TDMA	:	Time Division Multiple Access

1 INTRODUCTION

This section serves as the thesis's introduction and provides background reading for the subsequent discussion of the results. The development of systems and information on 5G vehicle networks are all included. This chapter concludes with a brief overview of the information in the next ones.

1.1 COMMUNICATION INFRASTRUCTURES

A communication Infrastructure consists of a grid of interconnected devices, known as nodes, that exchange data with one another. In the past, networks used cables to link nodes, but nowadays, wireless connections are the norm, with antennas mounted on each node to receive and transmit signals. The number of users and the types of applications any network must support cause a wide range in network size [1].

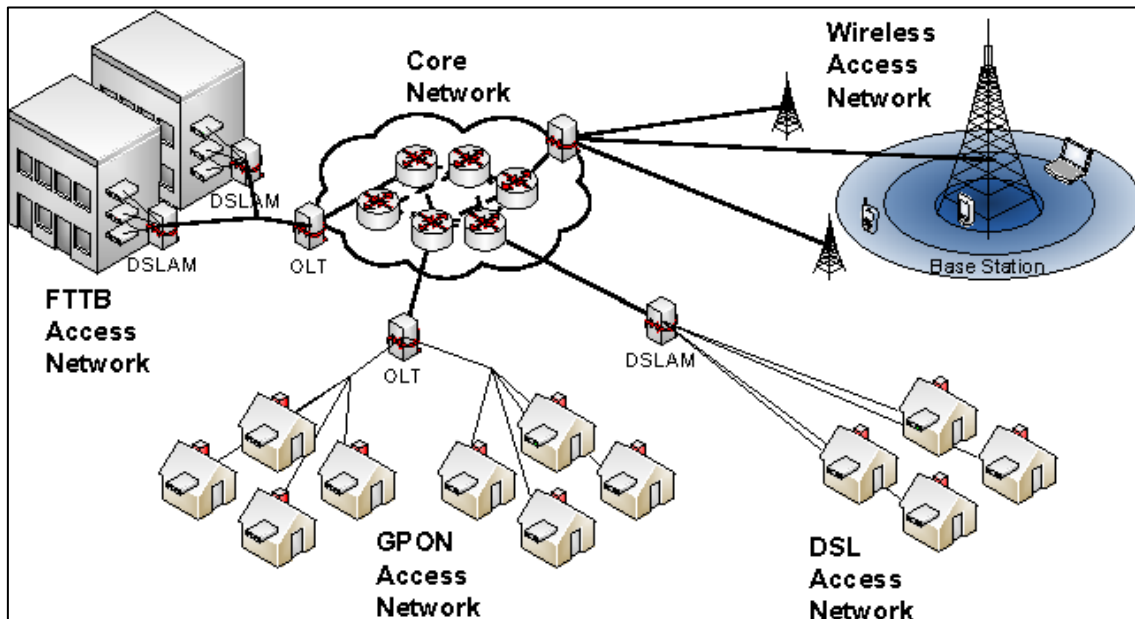


Figure 1.1: Instances of a Common Urban Communication Infrastructure [2].

An IP address is a number assigned to each device in a communications network that operates over the Internet as shown in

Figure 1.1: .1, this number is used to track the data's path through the network. The following buildings provide examples of this:

- a. In a WAN, devices may be located anywhere in the world and still be linked.
- b. In-building networks, or LANs, consist of devices located in the same physical location.
- c. Connected devices in a MAN span many different structures., i.e.

Mobile phones particularly highlight the importance of telecommunications networks since their development has paralleled that of mobile phones themselves [3]. The creation of international standards to govern and enhance these networks is exemplary proof of this. In order to improve its efficiency, stability, speed, and encryption, the so-called "first generation" of wireless technology has undergone many changes since its inception. This expansion followed the arrival of 3G and 4G networks. Due to advancements in packet switching and orthogonal frequency division multiplexing (OFDM), 4G has made it possible for the common user to enjoy a fast, reliable internet connection. The timeline of these networks can be seen in 1.2, and it's clear that the recently released 5G is taking over with an even greater level of performance that will match market expectations for years to come.

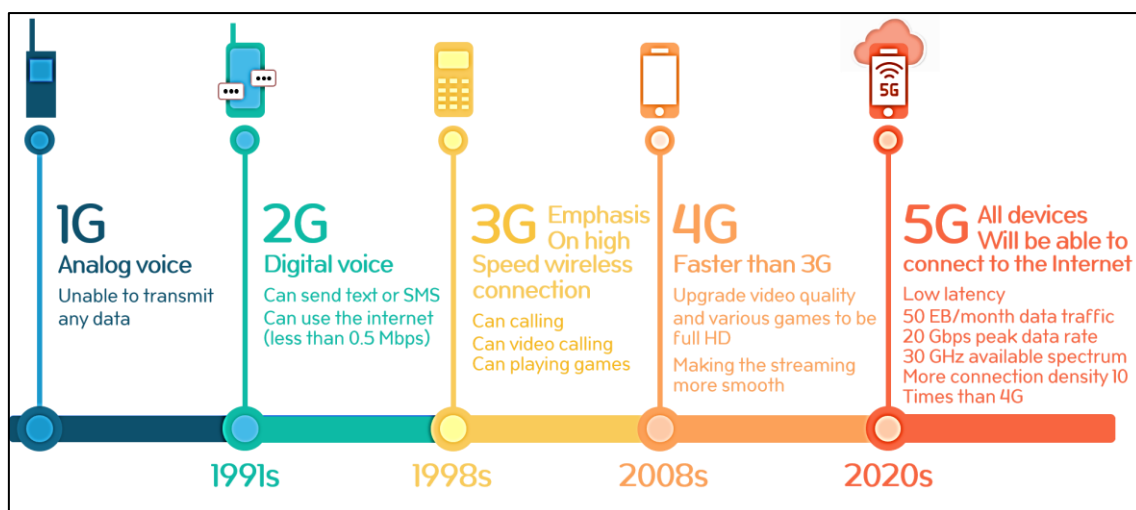


Figure 1.2: Technology improvements in wireless communication systems [4].

1.2 GROWTH OF 5G

5G is the most current generation of cellular networks, and it enables fast speeds and low latency by using technologies such as massive MIMO, edge computing, and intelligent beamforming. 5G is the most recent generation of cellular networks. In addition to this, there are newly discovered band spectrums that operate at very high frequencies and, as a result, are not as congested with users. The idea of 5G was first presented in 2016, yet it didn't become officially available to consumers until 2020.[5].

The rollout of 5G technology happened quite quickly since its primary objective is to meet the needs of consumers very soon. In 2019, 5G chipsets were commercially accessible, and in 2020, mobile phones that could operate at 5G became commercially available [6]. Statista's research resulted in the creation of the bar chart that is shown here in Figure 1.3. This figure depicts the increase that was computed for the usage of 5G. It is unavoidable that the number of people using 5G will expand at a breakneck pace.

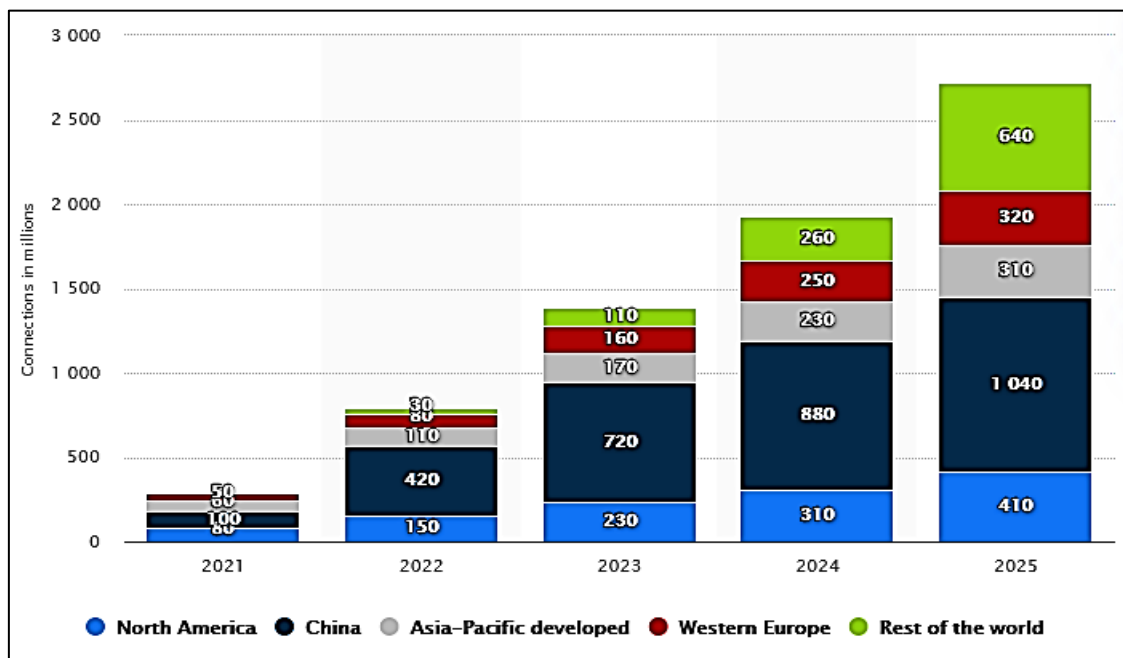


Figure 1.3: The anticipated number of 5G subscriptions around the globe [7].

When compared to earlier forms of communications technology, 5G's enhanced frequency band utilization results in a higher level of operational efficiency. Sharing of the spectrum is the approach that is used to accomplish this. Spectrum sharing is a relatively new antenna technology that makes it possible for numerous devices to utilize the same frequency bands at the same time. In the meanwhile, the new very high-frequency bands, which will operate on waves known as mm-Waves (millimeter waves), will make more space available for customers who are just beginning to join the market. Due to its frequency range of up to 300 GHz, it is able to accommodate future users for many years to come, as can be seen from the various use cases that are provided in Figure 1.4.

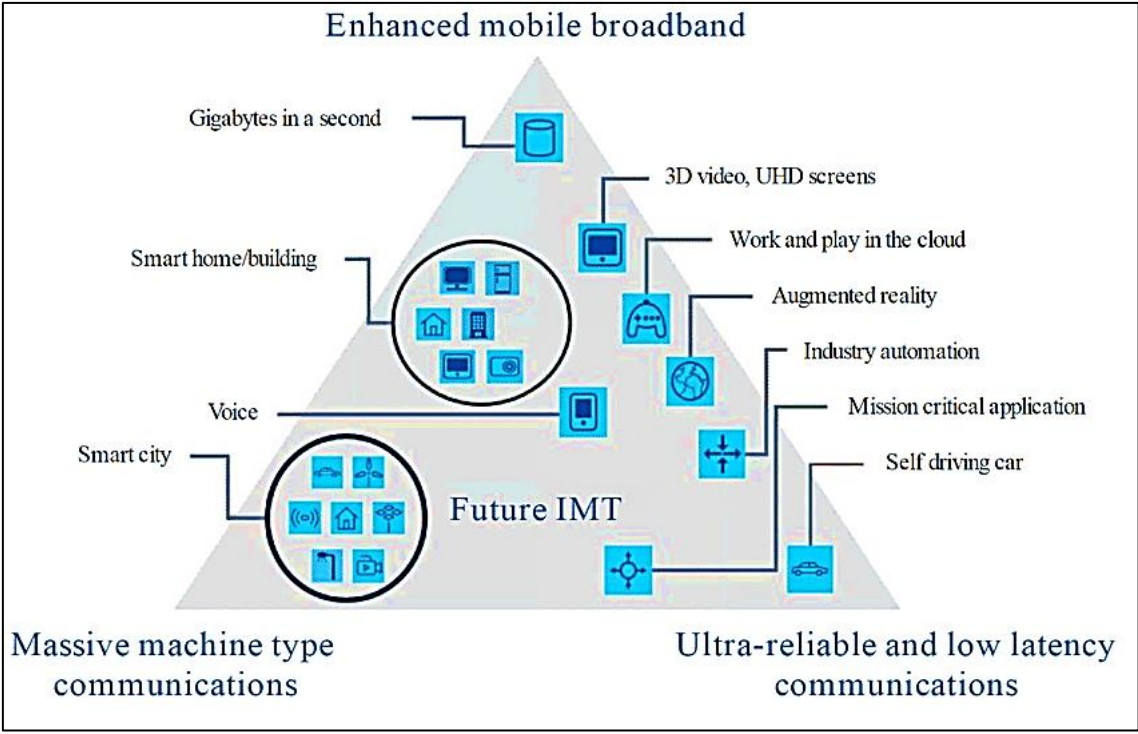


Figure 1.4: 5G use cases[8].

Because of its acceptable speed and latency, the 5G network will serve as the foundation for the development of a wide variety of important applications, including self-driving vehicles and health care management systems. IoT (Internet of Things) applications, smart city development, and biometric application use will all see significant growth thanks to 5G[9].

1.2.1 5G Enabling Techniques

A-millimeter waves

The fifth generation (5G) mobile communication networks may now access new facilities with a massive quantity of spectrum via the millimeter wave (mmWave) bands to meet the uncontrollably rising demand for mobile data. Directivity, susceptibility to obstruction, and significant propagation loss are important distinctions between mmWave communications and conventional systems that must be considered.

The bandwidth in the 5G network is between 30 GHz to 300 GHz as shown in Figure 1.5, meaning that the wavelength is from one to ten millimeters, which depends on the length and size of the antenna, and the smaller the wavelength, the smaller the antennas we need.

millimeter waves advantage:

- a. Increasing the bandwidth
- b. Achieving a high data transfer rate
- c. Improving security and privacy because they are waves directed in a specific direction
- d. Connecting the towers with each other without the need for optical fibers and thus reducing the cost.

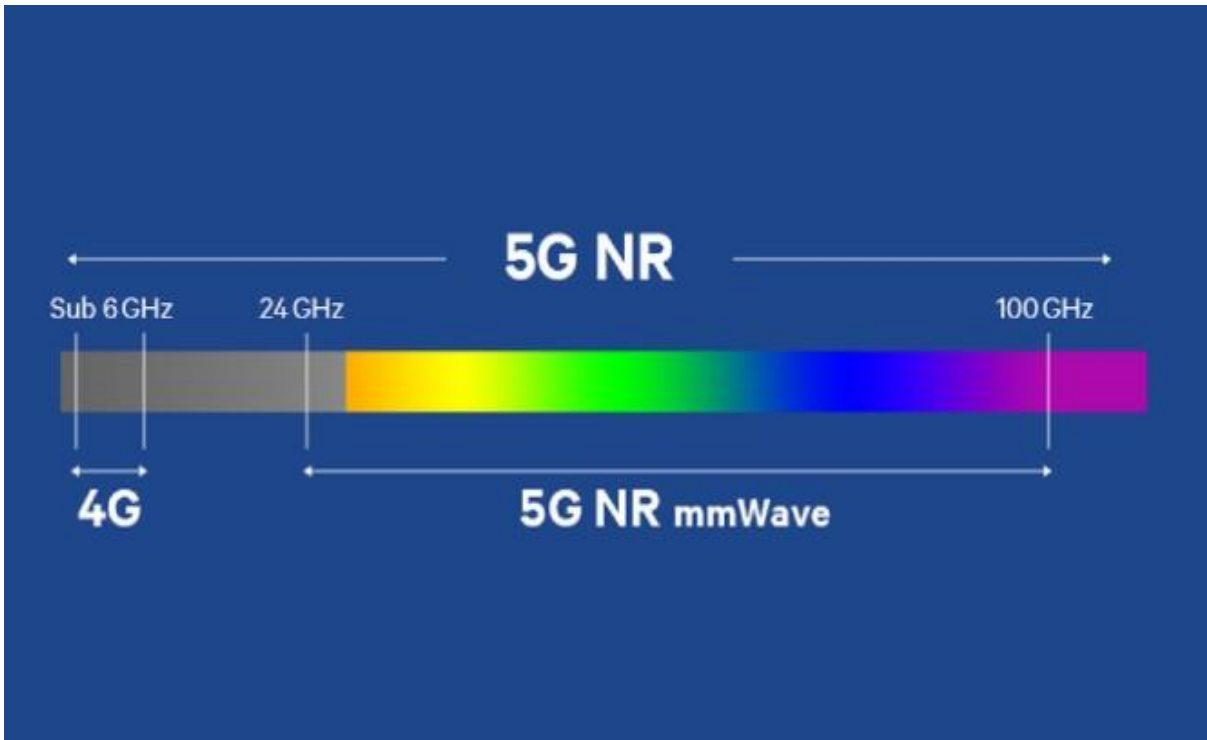


Figure 1.5: Millimeter waves[10].

B-Small cells:

A network that is capable of increasing data transfer rates and energy efficiency while simultaneously reducing latency and interference may be established by densifying the urban environment with mobile small cells and allowing direct-to-device (D2D) communications via network offloading. On the other hand, the growth of normal, small cells may be responsible for the majority of these advantages [11]. Because the strength of a radio signal lessens proportionately with the square of the distance traveled, it is possible to conserve a significant amount of energy by switching from one longer transmission to a number of shorter transmissions that are sent to and from the base station (BS). In a manner analogous to this, signals that are shorter and weaker would result in less interference, allowing for quicker throughput and thus greater data rates. Lower latency may be obtained when a source node (SN) and a destination node (DN) are connected through a path that is more directly connected to one another (DN). However, mobile small cells also provide some advantages to their users. They may be instantaneously set up, depending on demand, anywhere, at any time, using presently

accessible mobile devices or Remote Radio Units. This is possible in any location (RRUs). The many forms of microorganisms are shown in Figure 1.6.

It is a small cell that covers a certain small area, it is of the plug-in-play type, and it has a limited capacity, as one cell can accommodate less than 128 users, as well as it covers a certain area from several meters to several hundred meters.

Advantages of small cells

- a. They consume less energy
- b. The user uses less energy
- c. Increasing the capacity and coverage through its widespread and thus increasing the devices connected to the network

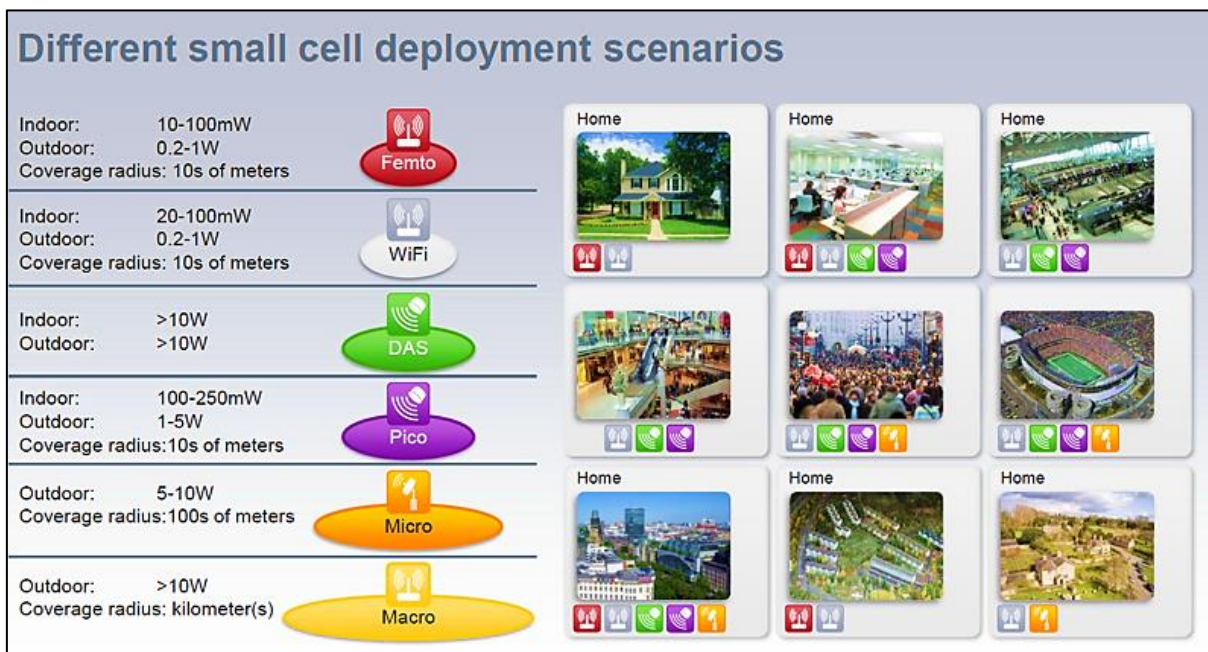


Figure 1.6: Small cell types[12].

C-MIMO

Most intriguing is the massive multiple-input multiple-output technology, which can meet the requirements of 5G and future networks (MIMO). Utilizing a vast number of antennas that are all connected to a single base station, Massive MIMO is an advancement on the original MIMO technology. The system's throughput and spectral efficiency are both improved as a result of this. The next generation of 5G networks will benefit from the integration of antennas, radios, and bandwidth thanks to this technology [13]. Because of its capacity to increase both throughput and spectrum efficiency, the Massive MIMO technology is quickly becoming an essential component of emerging wireless standards. In this scenario, the significant array gain that massive MIMO is able to achieve with a large number of antennas is the determining factor, as seen in Figure 1.7. Most intelligent sensing systems rely on the proper functioning of 5G, and this is only possible thanks to Massive MIMO. Using conventional multi-access methods to collect data from the massive array is problematic due to the resulting lengthy latency, poor data rates, and reduced dependability. Using massive MIMO, we can recognize data from continuous sensor transmission while drastically reducing latency. It can also improve data speeds and offer stable connectivity for sensors. Other examples of smart sensor applications include smart grids, smart antennas, and smart highways. The information obtained by intelligent sensors will need to be sent in real time to be centralized monitoring sites in order for these sorts of applications to work properly. Because the number of antennas in one base station in a 4G system was only 16, but the number of antennas in one base station in a 5G system can reach 300, the purpose of this technology is to dramatically increase the number of users by expanding the quantity of the antenna array in the base station. The 4G system only had 16 antennas in one base station, but the 5G system has 300 antennas in one base station. Increasing the total number of antennas present in the base station will be the means by which this goal will be achieved.

Advantages of MIMO:

- a. Increased single bath
- b. Increased data transfer rate
- c. Increased reliability

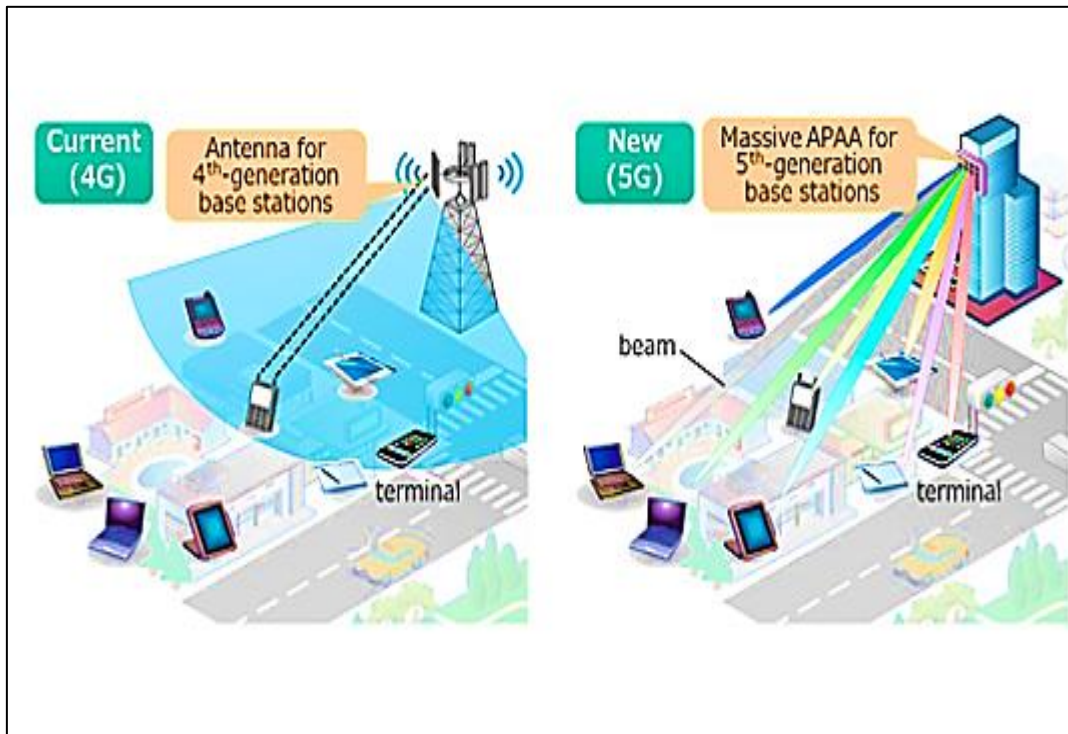


Figure 1.7: MIMO in 5G[14].

D-Beamforming

The regulated interference of a great number of waves is what constitutes the process of beamforming, which raises the signal strength in the direction that is wanted. Combining a large number of transmitting antennas with a variety of phase shifts is one method that may be used to achieve this capability. However, a circular (or non-directed) structure can only be effective in situations when the need for traffic is constant, which almost never occurs in real life. Establishing the current positions of the users is a necessary step in the process of selecting the optimal antenna irradiation pattern for each base station.

It is a technique used to focus the beam in a specific direction where the beam angle is from 3 degrees to 30 degrees. The direct of the beam is controlled by the time delay between the several antennas; hence, more antennas result in a narrower beam. Through, and implement beam formation in both the digital and analog domains. the use of the antenna array, we can create numerous links at once, alter the direction of the links quickly enough to keep up with the speed of the moving objects

Advantages of the beam:

- a. Increasing the transmitted power
- b. Decreasing the interference between signals
- c. Increasing the distance that the beam reaches as shown in Figure 1.8
- d. Reducing energy consumption

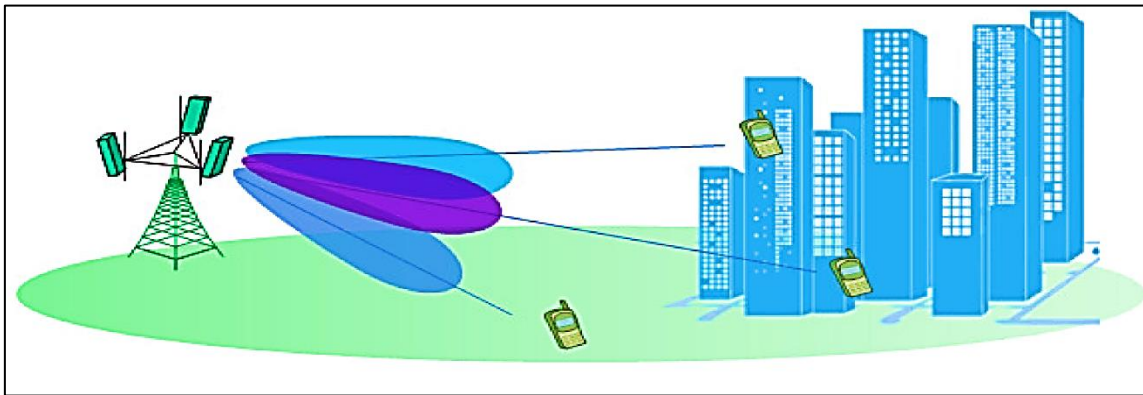


Figure 1.8: Beamforming technology[15].

E-Full duplex

A full duplex is a way that may be used in 5G networks to modify the duplexing paradigm. This approach is also known as a full duplex. The technique of self-interference cancellation makes it possible to cut down on the amount of time needed to allocate resources and to increase the effectiveness with which channels are used. These benefits are made possible as a result of technology. When used in a mobile network, the full duplex approach, on the other hand, has the potential to cause issues with cross-link interference across the different network entities. In point of fact, it is vital to handle these new sorts of interference in order to properly manage the scheme's integration into the network in order to achieve the desired results. On the other hand, the diversity of expanding 5G networks, which are squaring off against the challenge of meeting unprecedentedly broad demands, makes it possible to investigate the possibility of full duplex operation at a newly developing network entity type known as the integrated access and backhaul (IAB) node. This is an exciting development. In point of fact, there is a possibility that this will be the first of many network adoptions for the plan. Another newly emerging use case,

the non-terrestrial network, may be the one that comes next to benefit from the use of duplex resources to their full potential. With regard to the standardization of responses, The number of cross-link interference management methods has been established by 3GPP in order to enable the integration of the system at the network infrastructure level and pave the way for subsequent stages of user equipment adoption. This methodical rollout of the network ensures that the self-interference canceling technology will eventually reach the required level of technical maturity. The requirements for self-interference cancellation are determined, from a more pragmatic standpoint, by the kind of device as well as the environment in which it is deployed. We offer experimental research findings of self-interference channel measurement addressing the outdoor deployment situation of an IAB node to evaluate the viability of full duplex adoption in the IAB use case.

It is to send and receive data at the same time by overcoming self-interference using SIC technology.

There are three types of transmission mode methods:

- a. Simplex: one-way transmission
- b. Half duplex: communication in both directions; nevertheless, it is not feasible to send and receive information at the same time
- c. Full duplex: two-way transmission at the same time as shown in Figure 1.9.

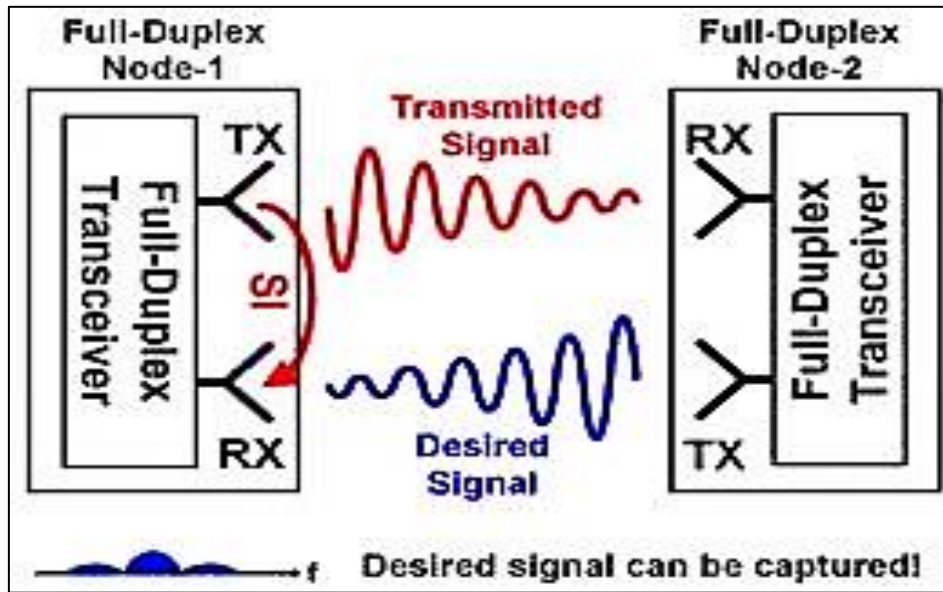


Figure 1.9: Full duplex[16].

F- Smart Antenna

The communication system will employ smart antennas to improve efficiency. The variety of transmitters and receivers (source and destination) in wireless systems is exploited by the smart antenna. To decrease communication error and boost transmission speed, diversity refers to the employment of different radio frequencies for transmission and reception as shown in Figure 1.10. This kind of technology has already been recognized as being significant in the majority of wireless systems, where signal-processing techniques will be utilized with antenna arrays to detect and track various wireless targets, such as cellphones. Additionally, it is utilized to determine the vectors for the beam design and the signal's direction of arrival (DOA).

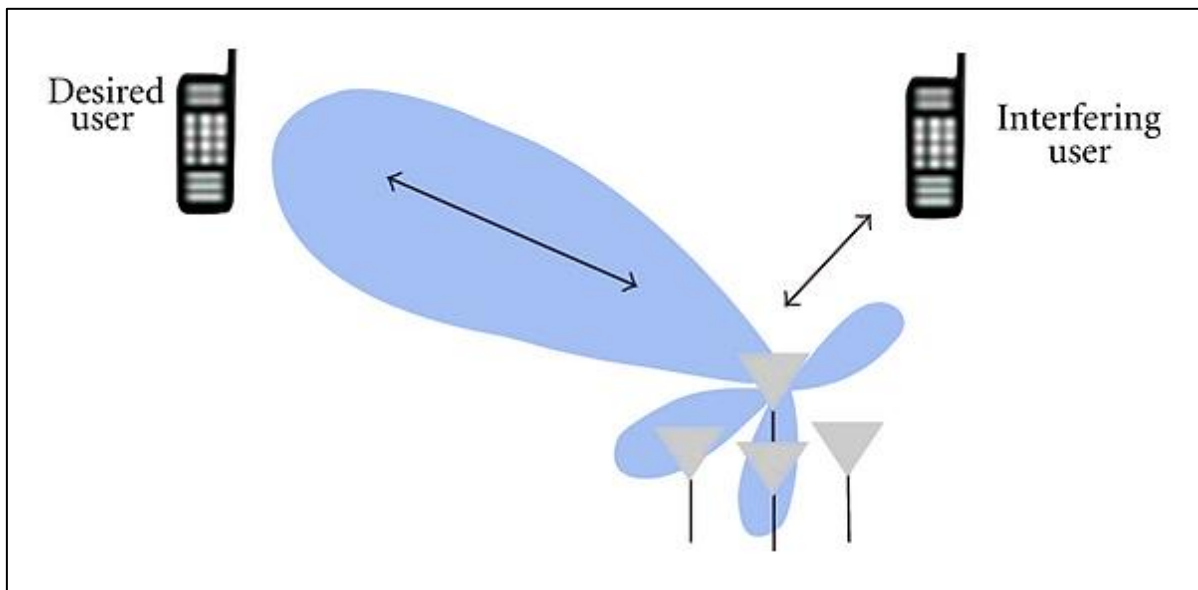


Figure 1.10: Smart antenna technology[17].

1.2.2 The Most Important New Applications in the Fifth-Generation System

- a. Augmented Reality: is virtual information that is combined with real objects to appear as if they are in the real world.
- b. Virtual Reality: simulates a digital environment
- c. Mixed reality: its usefulness is the interaction of reality with the digital environment, and it is very useful in the field of medical education in addition to other sciences
- d. Virtual Games
- e. Monitoring and Inspection: The ease of communication of surveillance cameras with each other and the speed of communication with the possibility of accommodating a huge number of cameras provides an integrated and accurate system
- f. Fixed wire access: This service allows communication between vehicles directly without the need to communicate through the base station
- g. V2X concept

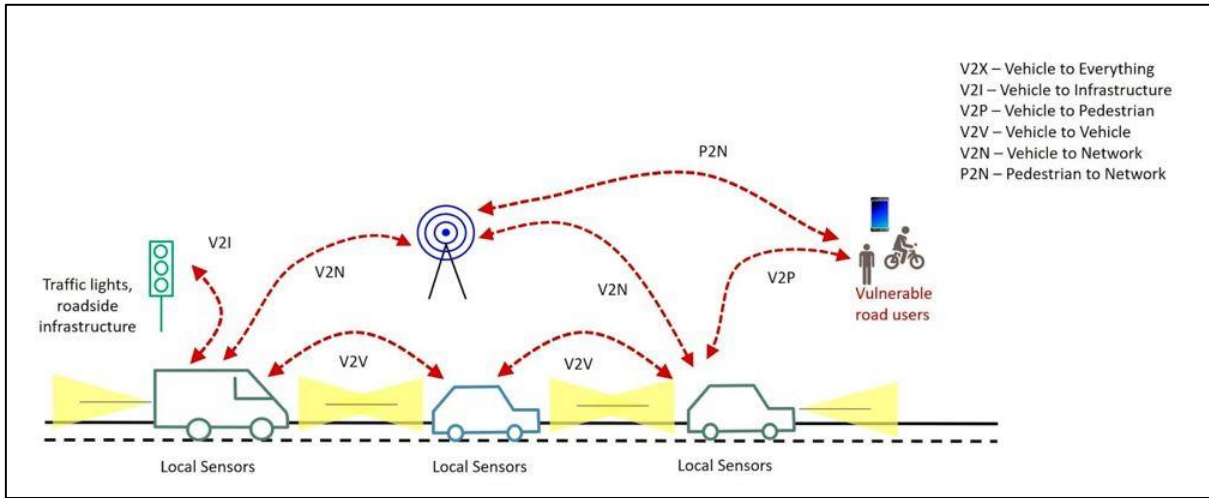


Figure 1.11: New applications in the 5G system[18].

- h. Privet and industrial networks: This technology is used in modern factories, as it allows robots to communicate with each other to organize their work easily and with high accuracy. Figure 1.11 is illustrated new applications in the 5G system.

1.3 THESIS OUTLINE

Using (CA-NOMA) technology to boost data transfer rates is one topic covered in this thesis; another is the use of artificial intelligence to enhance the efficiency of the (CA-NOMA) protocol during the network's power-up phase. This thesis provides an in-depth analysis of each of these approaches. In this paper, we focus on MobileNetV2 and NasNETmobile, two types of convolutional neural networks, and compare and contrast their abilities in terms of integration and performance.

This section outlines the thesis's timeline.:

- a. (CA-NOMA) Technology
- b. Conducting content analysis on the linked papers and events with (CA-NOMA) Technology
- c. Analyzing papers and proceedings associated with (MobileNetV2 and

NasNETmobile)

- d. Design the code of (MobileNetV2 and NasNETmobile)
- e. Simulate the code of (MobileNetV2 and NasNETmobile)
- f. Analyze the results
- g. Compare the results

As such, the next chapter provides a literature evaluation of relevant scientific findings that may be used as a basis for future research into ways to enhance the (CA-NOMA) system. Next, we'll talk about the information and approach that went into developing CA-NOMA and the results that were found. Finally, the book wraps up with a discussion and conclusion chapter that recaps the thesis's methodology, draws conclusions from the thesis's study, and discusses what comes next.

2 LITERATURE REVIEW

This chapter provides context and an outline of the thesis, discussing the fundamental concept of NOMA and its impact on the evolution of wireless communication networks. Also discussed are the benefits and drawbacks of caching, as well as the difficulties of expanding its capacity, particularly when used in tandem with NOMA.

2.1 CACHING

Wireless caching is a content-centric networking technique that can help 5G cellular networks meet the massive downlink capacity demands of video streaming. Recently, it has been suggested that UEs like smartphones and tablets employ caching to increase streaming QoE while decreasing (i.e. offloading) cellular data use. Cache placement and delivery are complicated since the total cache capacity is spread among devices that don't work together and have limited cache memory. Because users are always on the move and making requests on the fly, it might be difficult to anticipate the true needs of the UEs throughout the cache installation process. Coded caching has been proposed in the literature as a viable solution for caching at UEs [19],[20]. Through the use of the cached data as ancillary information, a coded multicast format is devised for the simultaneous error-free broadcast of video to many users, resulting in a multiplicative performance improvement that scales with the total cache memory capacity of the UEs. In contrast, the computational cost of controlled caching increases exponentially with time. Furthermore, caching methods perform best over wired networks and other error- and noise-free communication channels. In wireless networks with fading and noise, however, the weakest user in the multicast group will limit the performance of the coded multicast[21].

Cash is one of the new technologies that are considered to be part of the 5G network. Cash is installed in each vehicle and helps to store the necessary information about other vehicles or on the road. This information is provided by the base station during non-peak times, and the vehicle can use the information during peak times, which reduces the load on traffic. Cash is one of the new technologies that are considered to be part of the 5G network. Because the memory travels via the base station in two stages, which leads to an increase in the data transmission rate as well as an improvement in the spectrum's utilization rate, the memory passes in two phases as

follows: 1- The period of caching During this phase, the information that is being given by the base station is being stored in the cache at a period that is not considered to be high use. The cache is where the information that is being utilized the most is stored. 2- The request phase, also known as the peak time phase, this phase is when the vehicle takes benefit of the information that is stored in the vehicle cache or the cache that has been put in other cars that are close without going back to the base station [22],[23].

2.2 NON-ORTHOGONAL MULTIPLE ACCESS (NOMA)

Because of its increased data transmission rate and decreased power consumption, this technology is essential to the 5G network. Many users may talk to one another at once while sharing the same finite amount of wireless bandwidth if a multiple-access technique [24] is used. By using a separate domain, like electricity or code, NOMA enables the allocation of several users to the same frequency and time resources. Signal pathways that aren't perpendicular to one another are more likely to cause interference for both users. Further classification of "NOMA" into "power domain NOMA" and "code domain NOMA" is possible. Code-domain NOMA encompasses a wide variety of access protocols, such as sparse code multiple access (SCMA), low-density spreading code division multiple access (LDS-CDMA), and multiuser shared access (MUSA). Code domain NOMA, which is based on the CDMA principle, could provide spreading gain and shaping gain at the cost of additional bandwidth. The SCMA is an enhanced version of LDS-OFDM that takes use of sparse nonorthogonal spreading to allow for many connections. By directly translating bit streams to various sparse codewords, this method allows users to multiplex many codewords utilizing a single set of orthogonal resources. Users may multiplex many codewords utilizing a single set of orthogonal resources using this method owing to a direct mapping of bit streams to various sparse codewords. Using a message-passing algorithm (MPA) [25],[26] enables multi-user identification at the receiver. Uplink MUSA is a derivative of multi-carrier code division multiple access (MC-CDMA) that employs complicated low correlation spreading sequences to distribute symbols throughout a network that operates on the principle of resource sharing. Implementing SIC at the receiver helps it get the data for each user [27]. Because of the large user overloading factor, the MUSA approach may significantly improve system performance. Enhancing spectral efficiency, power domain

NOMA uses superposition coding (SC) at the transmitter to multiplex the users' signals in the power domain and successive interference cancellation (SIC) at the receiver to identify the users' signals. When considering UE mobility and the feedback delay of channel status information (CSI), power domain NOMA may provide a progressive performance gain [28]. Before assigning transmission power or pairing users, the transmitter must have knowledge of the receivers' channel state information (CSI). The CSI, however, is required for user demultiplexing in the receiver [29]. Since orthogonal multiple access (OMA) has a lower spectrum efficiency and a smaller capacity than non-orthogonal multiple access (NOMA), the non-orthogonal multiple access (NOMA) protocol has emerged as a front-runner in the race to further improve the capacity and efficiency of mobile networks of the fifth generation (5G) [30]. NOMA is used on the transmitting end to superimpose the signals of several users in the power domain; sequential interference cancellation (SIC) is used on the receiving end to decouple the signals. NOMA is employed at the transmitter end. As the world's energy needs grow, it's critical that we come up with effective strategies to overcome them. One such strategy is the Network-Oriented Multiaccess Access (NOMA) protocol, which improves the system's performance by giving the remote user more power and the nearby user less, thereby reducing overall energy use and promoting fairness among users [31],[32].

consider one BS and K users. The total bandwidth B_T , The B_T have N channels of equal bandwidth B , the channel gain of users, *i. e.*, $|h_{1,n}|^2 < |h_{2,n}|^2 < |h_{3,n}|^2 \dots \dots < |h_{k,n}|^2$, the power transmission is P_T , and the fraction is $(0 < \alpha_{k,n} < 1)$, NOMA support several users to be sent by a single channel, While in the OMA system, more than one user cannot participate in one channel. To ensure fairness between users, the higher power is assigned to the remote user (*i. e.*, $\mathcal{P}_{1,n} > \mathcal{P}_{2,n} > \mathcal{P}_{3,n} \dots \dots > \mathcal{P}_{k,n} > 0$). We can obtain a bit rate for user k at each $channel_n$ as follow in eq (2.1), (2.2),(2.3):

$$R_{k,n} = B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{|h_{k,n}|^2 \sum_{i=k+1}^K P_{i,n} + BN_0} \right) \quad (2.1)$$

the bit rate of UE_1 and UE_2 are shown respectively in eq (2.2), (2.3):

$$R_1 = \log_2 \left(1 + \frac{P_1 |h_1|^2}{P_2 |h_1|^2 + N_0} \right) = \log_2 \left(1 + \frac{\alpha \Gamma_1}{(1-\alpha) \Gamma_1 + 1} \right) \quad (2.2)$$

$$R_2 = \log_2\left(1 + \frac{P_2|h_2|^2}{N_0}\right) = \log_2(1 + (1 - \alpha)\Gamma_2) \quad (2.3)$$

Where Γ_1 and Γ_2 are signal-to-noise ratios for UE_1 and UE_2 respectively. Since it is impractical to allow all users to use the same channel simultaneously, OMA divides each time slot into two parts, one for User Equipment δ for UE_1 and one for User Equipment $(1 - \delta)$ for UE_2 . Using the following equations (2.4) and (2.5), we can calculate the bit rate for UE_1 and UE_2 , respectively:

$$R_1 = \delta \log_2\left(1 + \frac{P_T|h_1|^2}{N_0}\right) = \delta \log_2(1 + \Gamma_2) \quad (2.4)$$

$$R_2 = (1 - \delta) \log_2\left(1 + \frac{P_T|h_2|^2}{N_0}\right) = (1 - \delta) \log_2(1 + \Gamma_2) \quad (2.5)$$

UE_1 's rate can be increased by allocating higher power P_1 , but it is limited by the signal strength of interfering UE_2 who is assigned power P_2 .

The rate of UE_2 is purely dependent on the allocation of power to UE_2 , as shown in 2.1. As a result, by managing the power allocation ratio $P_1 = P_2$, Optimization of the total throughput and user equality are both possible [33].

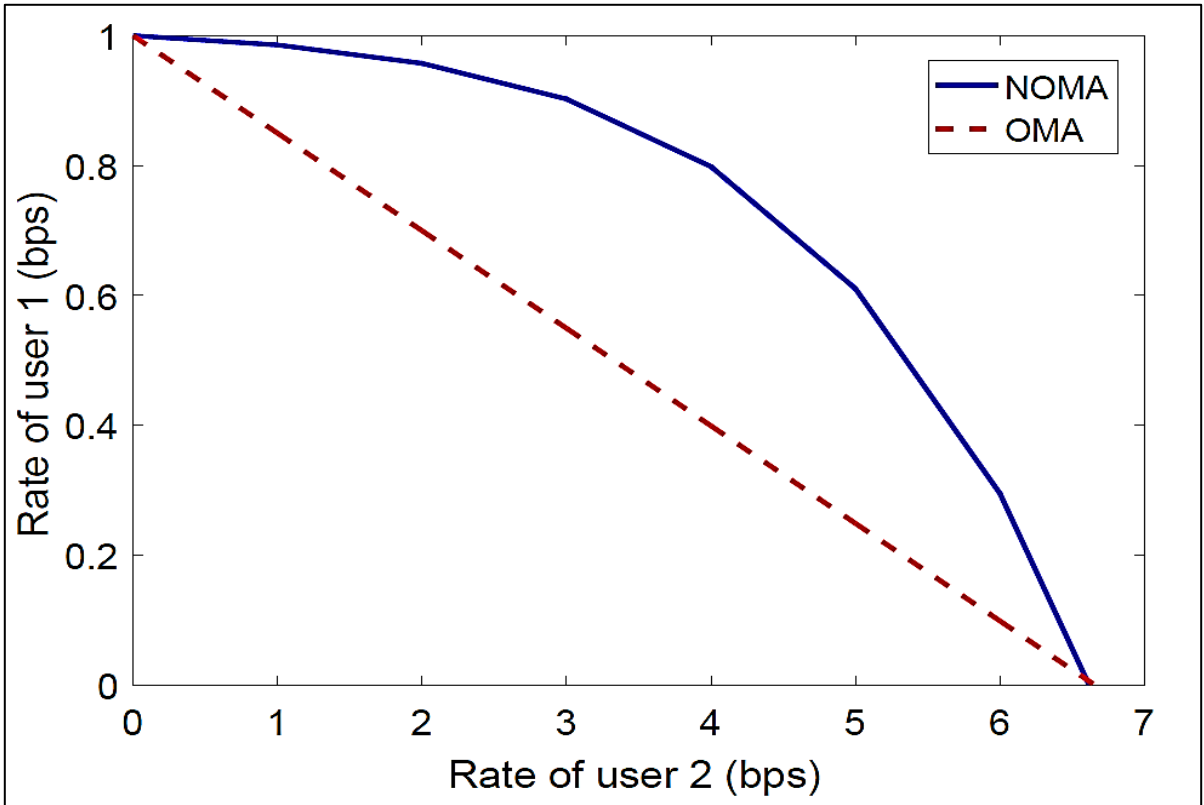


Figure 2.1: Bitrate of downlink NOMA and OMA[34].

By strategically matching users with considerable variances in channel gain, NOMA is possible to get multiplexing advantages. As a result of power-sharing, users get more bandwidth at the cost of reduced power. Whereas OMA technology restricts the number of concurrent users on a single frequency and thus the amount of data that can be sent over that channel. Take a look at Figure 2.7 to see how NOMA and OMA compare in terms of bitrate and keep in mind that if the SNR of UE_1 and UE_2 is known to be 0 dB and 0 dB, respectively, and if $\alpha = 0.8$ and $1 - \alpha = 0.2$ are assumed, then the transmission rate of NOMA UE_1 and UE_2 are $R_1 = 0.74 \text{ bps}$ and $R_2 = 4.39 \text{ bps}$.

For OMA, UE_1 and UE_2 both have a transmission rate of $R_1 = 0.50 \text{ bps}$ and transmission rate of $R_2 = 3.33 \text{ bps}$, with R_1 and R_2 having the same value (i.e., =0.5) for OMA. The basic example shown here shows that compared to OMA, NOMA provides more user throughput and a higher bit rate. NOMA is unquestionably better than OMA in terms of user bandwidth and bit rate.

Using the whole timeslot improves performance, as shown in (2.2) and (2.3), despite degradation due to interference with UE 1 and reduced power provided to UE 2. OMA's already low spectrum efficiency is lowered when resources (here, timeslots) are assigned to clients with poor channel quality. Since the strong user may take advantage of all the resources that would normally go to the weaker user, spectral efficiency is improved in NOMA [35],[36]. By using consumers' unique channel advantages, NOMA is widely recognized as one of the most promising multi-access solutions for mobile networks, which helps ensure that all users have an equally beneficial experience [37].

The significant advantage offered by the NOMA system is the exploitation of the bandwidth, whereby each user is allocated a certain amount of power while subscribing to the same frequency, which allows a huge number of users to transmit data at the same frequency and time, thus increasing the capacity in the network. In the transmitting station, it depends on (SC) to send the users' data, where the (SC) Superposed the users' data depending on the difference between the power of each user without depending on the frequency[38],[39].

As demonstrated in Figure 2.2, where the resource provided to the various users is colored differently, there are substantial differences between the OMA and NOMA protocols with regard to resource distribution. The OMA protocols in Figure 4a give each user unique access to resources including time, frequency, and code. Since there should be no interference between users, a receiver can easily find each user's packet. The greatest number of users that may be served is therefore constrained due to exclusive resource allocation. The NOMA protocol, in contrast, distributes the same two-dimensional time-frequency resource among several users in the power domain. By making use of the properties of channel difference, the NOMA protocol allots the same resource, enabling several users with a large channel gain difference to share the resource[40][41]. As a result, there is no tight cap on the number of users that may be maintained. The NOMA protocol requires a complex user signal identification procedure called SIC at the receiver node side, in contrast to the OMA protocol. A large cell capacity is attained because each user may independently decode one packet from the superposed packets in the power domain using the SIC[42].

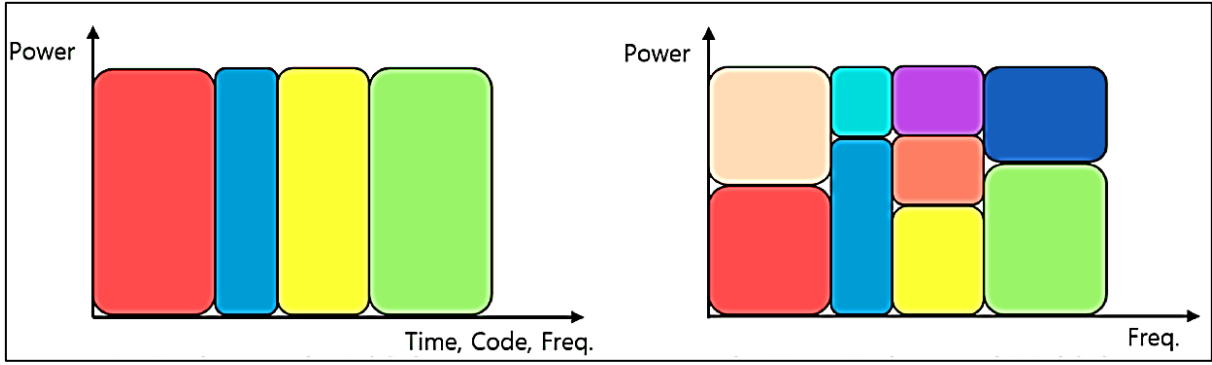


Figure 2.2: Sending data using OMA and NOMA technologies[43].

and in the receiving station, it depends on (SIC) to cancel interference between the signals and then get the Required signal.

2.2.1 Superposition Coding (SC)

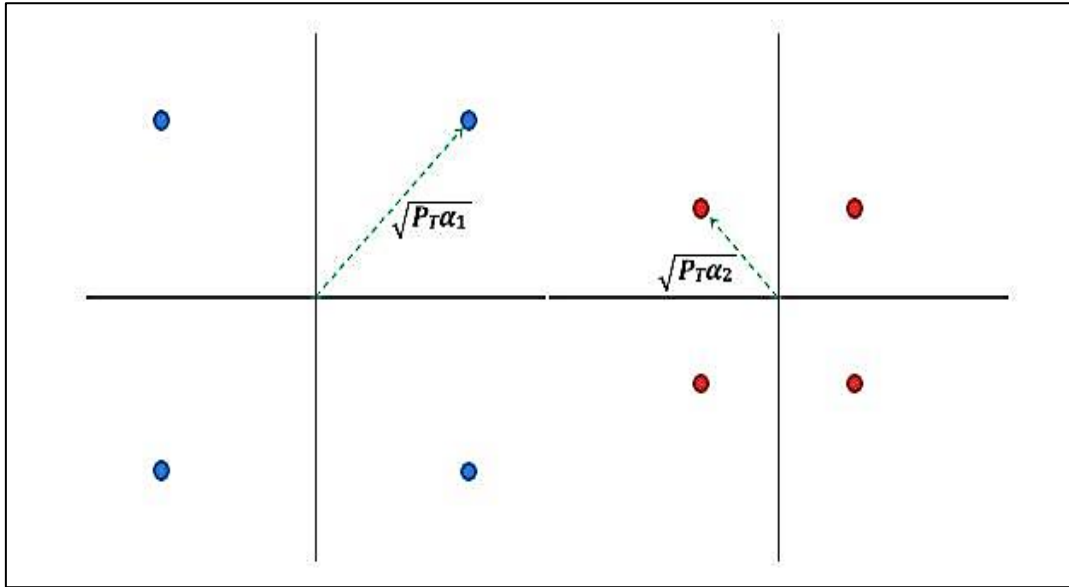
It is one of the basic technologies in the field of energy which is very important to understand the concept of NOMA because it transmits information of different users through one channel at the same time, or in other words, it superimposes different signals in the transmitter at the same time[44].

To simplify, we consider that the transmitter sends the information of two users, the (SC) combines the signals together in one channel as shown in Figure 2.3, we consider the use of the Quadrature Phase Shift Switch (QPSK) overlay, we consider that User 1 has the power higher transmission, and user 2 has lower transmission power, the power variance explains how SC works. For attaining amplitude on a scalar Gaussian broadcast channel, SC is a non-orthogonal strategy [45]. To construct the overlay constellation seen in Figure 2.3. (c), the SC constellations of Users 1 and 2 are simply laid on top of one another. As seen in eq (2.6), the overlay code for a user's status looks like this:

$$x_s = \sqrt{p_t a_1} x_1 + \sqrt{p_t a_2} x_2 \quad (2.6)$$

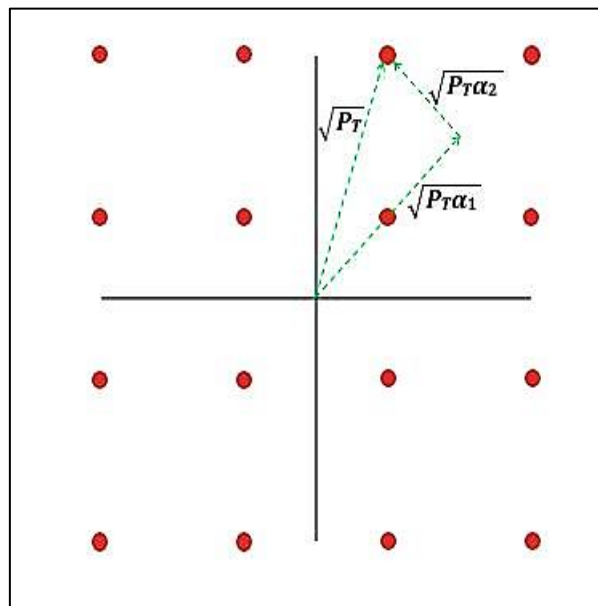
- a. p_t : total power
- b. a_i : fraction of the total power assigned to user i

c. x_i : signal of user i



(a) The signal from the first user

(b) The signal from the second user



(c) superposed signal

Figure 2.3: Superposition coding[46].

2.2.2 Successive Interference Cancellation (SIC)

In order to decode the superposed signal at the receiving end, the (SIC) method relies on the disparity in signal intensity between the overlapping signals [47],[48]. The way SIC is supposed to function is by first decoding the strongest signal and then decoding the weakest signal; after each signal has been decoded, it is subtracted from the combined signal until the desired signal is reached, and the other signals are ignored as noise. The signal that the user (κ) receives is indicated by

$$y_k = h_k(\sqrt{p_{t\alpha_1}x_1} + \sqrt{p_{t\alpha_2}x_2}) + w_k \quad (2.7)$$

where h_k is the complex channel coefficient at the user (κ) and w_k denotes the additive white Gaussian noise (AWGN). This case has two users, one with a stronger signal than the other ($\alpha_1 > \alpha_2$), and the other with a lesser signal. Since the signal from user 2 is disregarded at receiver 1, decoding the intended signal from the received signal y_1 occurs instantaneously. The signal coming from user 1 is first decoded by receiver 2. Let us assume that the receiver belonging to User 2 properly decodes the signal that was sent by User 1. In order to recognize signals coming from both users, as shown in Figures 2.4 and 2.5, we must first make use of the signal that was recovered from user 1 to subtract itself (as noise) from the signal that was received.

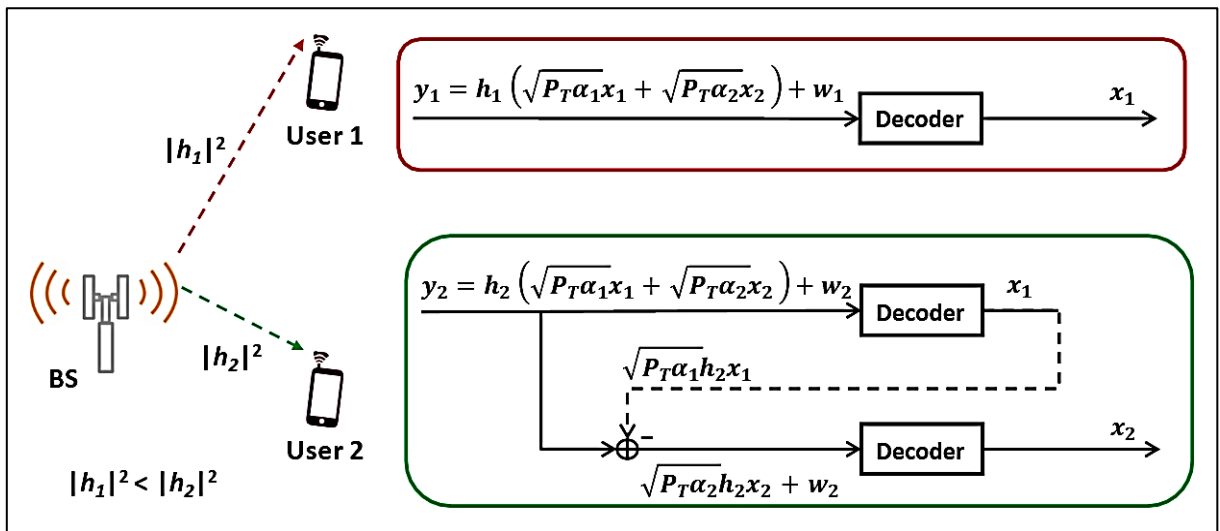


Figure 2.4: SIC procedure for a downlink situation involving two users [49].

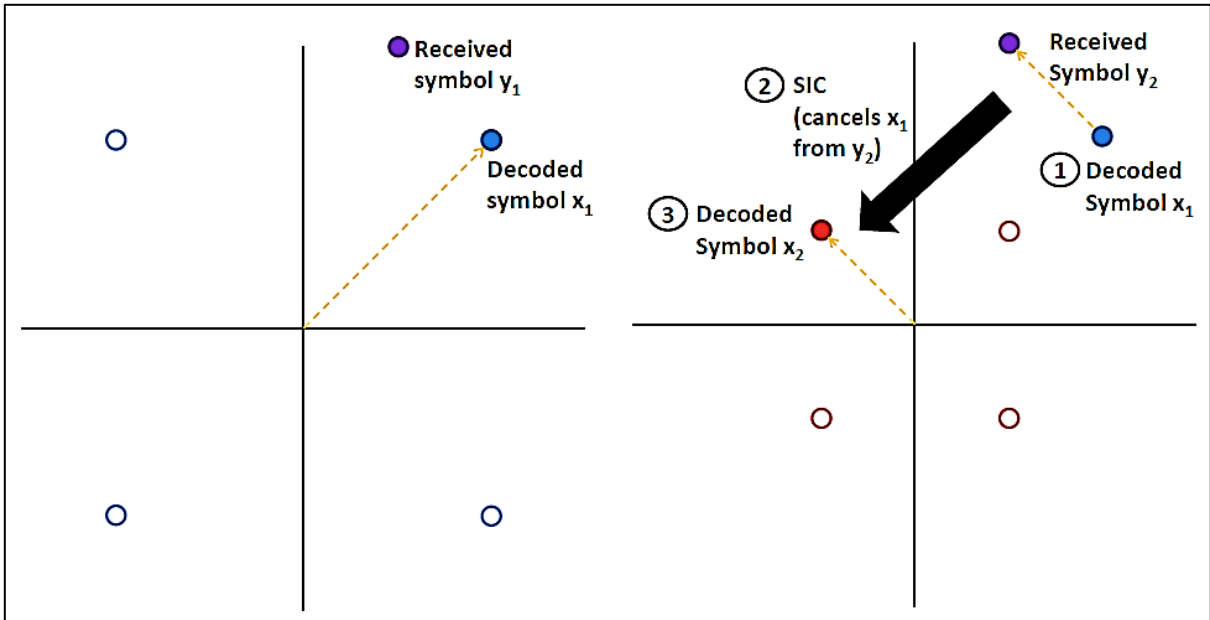


Figure 2.5: NOMA symbol decoding example [50]. (a) The decoding of the signal from the first user
 (b) The decoding of the signal from the second user

2.2.3 Cache-Enabled Interference Cancellation (CIC)

(NOMA) is considered one of the most promising solutions, where (SC) is used in the transmission and (SIC) in the reception, but with the massive increase in the number of users in the new system such as (MIMO), the (SIC) is considered somewhat slow due to its mechanism of action as it decodes the signal In order from the strongest signal to the weakest signal, and in order to deal with this problem[51], CIC has been integrated with it, as shown in Figure 2.6 it compares the received data with the data stored in the cache in advance and decodes the signal directly, and this means that the recipient is able to decrypt the strong and weak signal and cancel the interference directly provided That the information is stored in the cache in advance as shown in the figure, which gives fairness among users and leads to flexibility in the system and speed in performance.

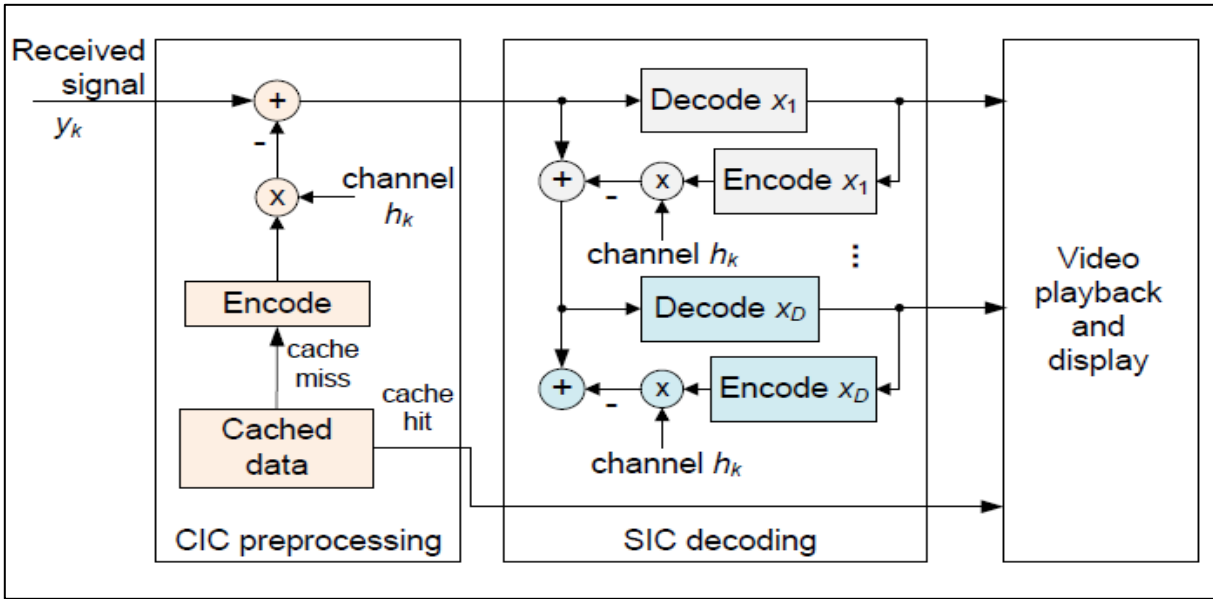


Figure 2.6: CIC Operation[52].

2.3 NEURAL NETWORK

Recently, reliance on artificial neural networks has increased due to their efficiency as solutions for a variety of tasks, including classification, clustering, pattern recognition, and prediction. One type of machine learning (ML) model, artificial neural networks (ANN), may currently compete with traditional regression and statistical models in terms of practicality [53]. Artificial intelligence (machine learning, neural networks, deep learning, and robotics), information security, big data, cloud computing, the Internet, and forensic science (ICT) are some of the most important and exciting topics in the field of ICT today [54]. The high speed and accuracy in dealing with data, as well as the time spent in data processing and the potential error rate are among the most important advantages of ANN [55]. There has been an increase in interest in this research field due to the potential benefits of fast processing of ANNs in large-scale parallel execution [56]. Artificial neural networks can be used for a variety of tasks, including but not limited to image recognition, processing big data, and performing many tasks simultaneously. To approximate universal functions in numerical models, artificial neural networks can be utilized in different fields because of the significant advantages they have of self-learning, adaptability, error rate, non-linearity, and handling of inputs with high accuracy.[57],[58].

Neural networks provide a number of benefits due to their efficiency in resolving both complicated and simple problems across a variety of domains. ANNs are capable of handling problems relating to agriculture, science, medicine, education, finance, administration, security, engineering, commodities trading, and technological matters. Included are problems with manufacturing, transportation, computer security, banking, insurance, property management, marketing, and energy, as well as any other problems that cannot be solved using traditional mathematics and standard procedural techniques. Also included are problems with any other fields in which such solutions are not possible[59],[60],[61]. Despite these widespread ANN applications, a methodical approach to ANN development is becoming more necessary in order to boost performance. The correctness of the data, the data instrument, the data standardization, the kind of data inputs, the division of the data, and the data pretreatment, validations, processing, and output procedures are a few important variables and issues that may be addressed[62].

Additionally, there are additional significant difficulties or problems associated with ANN modeling that have drawn attention and will need to be researched further in the future. Including development strategies that can enhance pattern transparency, improve the building of robust models, and enable knowledge from trained ANNs. Additional difficulties include finding innovative ways to deal with uncertainty and enhancing convergences. Additionally, noise and continuous gradient conundrum with variable issues are quantized[63]. It is necessary to apply quantization to solve the time-consuming and variable convergence problems that afflict most supervised-training ANS in order to solve the problem of traversing the error surface [64],[65],[66].

2.3.1 Neural Networks Applications

Given this explanation of neural networks, their mechanism of operation, and the numerous real-world issues that they have been used to solve in business, academia, economics, and other facets of daily life. Additionally, NNs may be used for data categorization, intrusion detection, and optimization methods[67],[68],[69]. Classification is thought of as a challenging sort of optimization problem. The bulk of studies that dealt with classification challenges employed machine learning (ML) techniques [70],[71]. Since NNs excel at identifying trends and patterns

in data, they are also useful for the aforementioned forecasting and prediction tasks. (Using Table 1 in the Appendices as a guide). Table 1 of the Supplement provides examples of how ANN has been successfully applied to real-world problems [72]. A variety of real-world applications of neural networks are covered, from modeling and classification to pattern recognition and prediction. Predicting a nation's financial stability is useful for planning the economy, government, and growth of any country. ANNs have also been used to foretell the success or failure of financial institutions and stock market forecasts. It's also used extensively in weather and climate forecasting, which improves the safety of people and the protection of property like buildings, the environment, installations, residences, and modes of transportation. Also, In the field of agriculture, one of the areas where neural networks have shown their utility is the classification of crops and fruits as well as obtaining accurate numbers of them using remote sensing. Viewed from this perspective, Supplementary Table 1 provides a high-level description of the great variety of problems that can now be addressed by this AI system.

Table 2.1: Shows the results of the use of ANNs for classification, pattern recognition, and prediction [73].

Examples of many fields of applications of ANN	Prediction	Pattern recognition	Classification	Total
Security	20	18	2	40
Science	25	25	2	52
Engineering	22	7	2	31
Medical science	10	5	2	17
Agriculture	3	3	2	7
Finance	10	15	2	27
Bank	5	15	2	22
Weather and climate	2	15	2	19
Education	30	15	2	47

Table 2.1: shows the results of the use of ANNs for classification, pattern recognition, and prediction
“tables continued” [73].

Environmental	10	15	2	27
Energy	5	15	2	22
Mining	2	15	2	19
Policy	2	15	2	6
Marketing	5	2	2	11
Management	5	4	2	12
Manufacturing	40	5	2	44

The topic of predicting artificial neural networks has received great attention from researchers, as artificial neural networks are one of the most important areas of artificial intelligence, so we find many concepts of artificial neural networks, but they share one goal, which is that the artificial neural network is a computational technique designed to simulate the way that leads The human brain has a specific task, it learns in a way similar to human learning through examples and training, and this is the core idea in the work of artificial neural networks[74].

Artificial neural networks have been continuously developed in many areas of life, such as economic and financial applications, applications of image and pattern analysis, as well as signal processing applications, and others[75].

Artificial neural networks consist of the input layer, through which the artificial network is fed with data, as well as the output layer through which the final results are output. There is a hidden layer between the input layer and the output layer, which receives the signal coming to it from the input layer and then sends it to the output layer.

The neural network consists of basic components as shown in figure 2.7

- a. Input layer: It is the layer through which the network is fed with data from the outside and the data is received by the processing units (neurons) that make up the network. For data, any neural network contains a layer of input.

- b. Output layer: This layer consists of the processing unit through which the final output of the network is output. This layer may contain one or more processing units according to the architecture of the network. The processing unit in the output layer receives the signal coming to it from the input layer directly or from the hidden layer. Performing the necessary processing may send a signal with the final outputs, or it may return these outputs as inputs back to the network when the required data processing is not performed.
- c. Hidden layer: this layer is located between the input layer and the output layer, and the hidden layer receives the signals coming to it from the input layer through the interfaces, then it is processed, and the necessary action is taken on it, and then sent through the links to the output layer.
- d. Interconnections (weights): They are communication links between the different layers that link the layers together or the units within each layer through the weights that are accompanying or attached to each interface. The task of the links is to transfer data or weighted signals between the processing units.

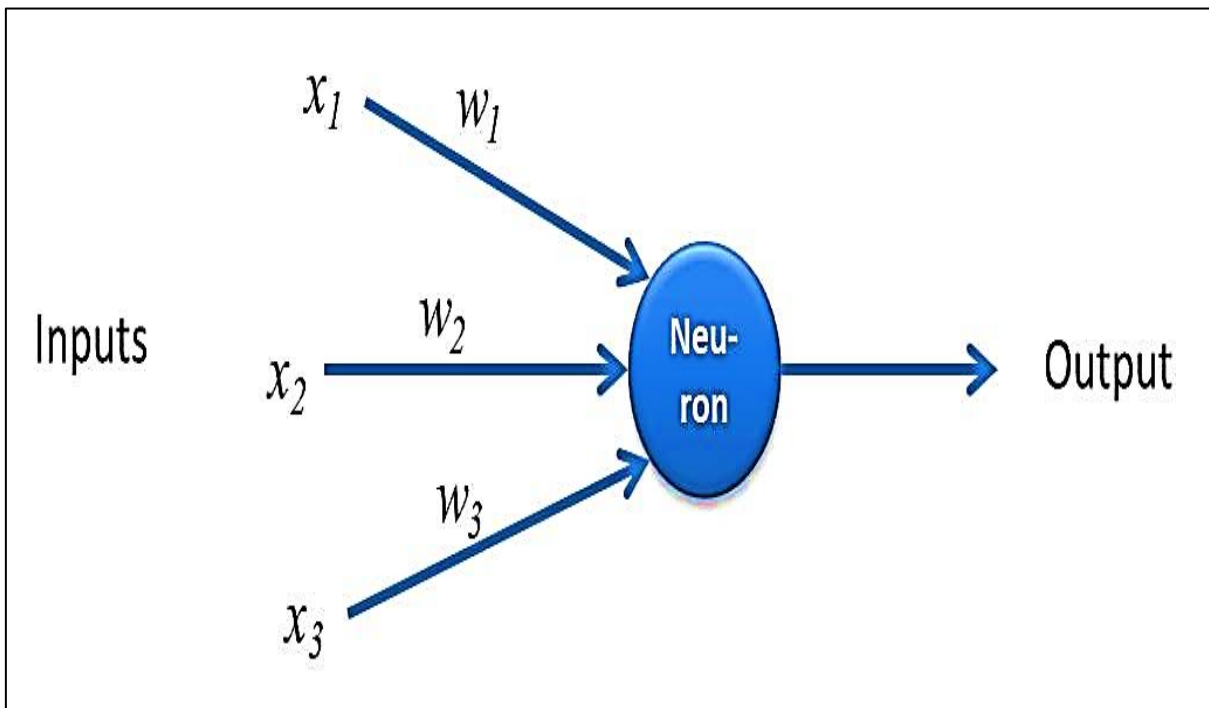


Figure 2.7: Simplified model of an artificial neural network[76].

Artificial neural networks have the following characteristics:

- a. It has a solid mathematical basis.
- b. It is a layer of IT intelligence that mimics the human brain and psyche in its operations.
- c. Take into account any information, quantitative or qualitative.
- d. Knowledge acquired from running instances on the network may be stored
- e. Several scientific disciplines may benefit from it
- f. It provides solutions that cannot be found by logical or ordinary methods used in traditional programs.
- g. Addressing the behavior of non-linearity so that it can find non-linear relationships between variables and take them into account in giving results.

2.4 CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network is a multi-layered neural network, each layer consists of multiple two-dimensional levels, and each level consists of several independent neurons. One of the great things about convolutional neural networks is that the receptive field and weight sharing reduce the number of parameters that the neural network needs to train, which helps improve the training performance of the general forward BP algorithm[77],[78].

Similar to conventional ANNs, convolutional neural networks (CNNs) are made up of neurons that train to maximize their own performance. The building blocks of innumerable ANNs, each neuron will continue to accept input and carry out an action (such as a scalar product followed by a non-linear function). The whole network will continue to express a single perceptual scoring function from the raw picture vectors used as input to the final output of the class score (the weight). The last layer will include loss functions related to the classes, and all of the standard techniques created for conventional ANNs are still applicable. The fact that CNNs are largely employed in the field of pattern detection inside pictures is the sole significant distinction

between CNNs and conventional ANNs. This enables us to include image-specific elements in the design, improving the network's suitability for image-focused tasks and lowering the number of setup parameters[79],[80],[81].

Biological nervous systems, such as the human brain, serve as a major source of inspiration for artificial neural networks (ANNs), which are computer processing systems. The primary building block of ANNs is a large number of interconnected computing nodes, or "neurons" which collaborate in a dispersed manner to learn from the input and maximize the output. An ANN's fundamental structure may be modeled. The input would be loaded into the input layer, which would then distribute it to the hidden layers, often in the form of a multidimensional vector. The learning process is when the hidden layers consider judgments from the preceding layer and determine if a stochastic change inside itself worsens or improves the output[82]. Deep learning is a general term for stacking up several hidden layers[83].

Convolutional Neural Networks (CNNs) excel at dealing with machine learning problems involving images, especially huge ones. Figure 2.8 is illustrated the major concept of CNN. A convolutional network can train after successfully reducing the dimensions of an image recognition problem to a massive data volume. Convolutional neural networks (CNNs) repeat feature differentiation, weight sharing, and convolution aggregation, reducing the order of magnitude of network parameters, and classical neural networks perform tasks such as classification. Given that we must pre-determine some parameters before training the model, such as the number of filters, filter size, network structure, etc., CNNs in practice learn the filter values on their own during the training process[84],[85],[86],[87].

Overfitting

Why does it matter, though? We could surely just add more hidden layers to our network and probably more neurons inside those levels as well. No, is the straightforward response to this query. The first is the obvious issue of not having infinite processing power and time to train these enormous ANNs[88],[89].

The second justification is to stop or lessen overfitting consequences. In essence, overfitting occurs when a network is unable to learn efficiently for a variety of reasons. It is crucial that

every effort be made to minimize its impacts because it is a crucial idea of most, if not all, machine learning algorithms[90]. We may observe a decreased capacity to identify generalized features for not just our training dataset but also for our test and prediction sets if our models showed symptoms of overfitting. This is the major cause of our ANNs' complexity reduction. The network is less prone to overfit with fewer parameters necessary for training, which naturally improves the model's ability to predict outcomes.

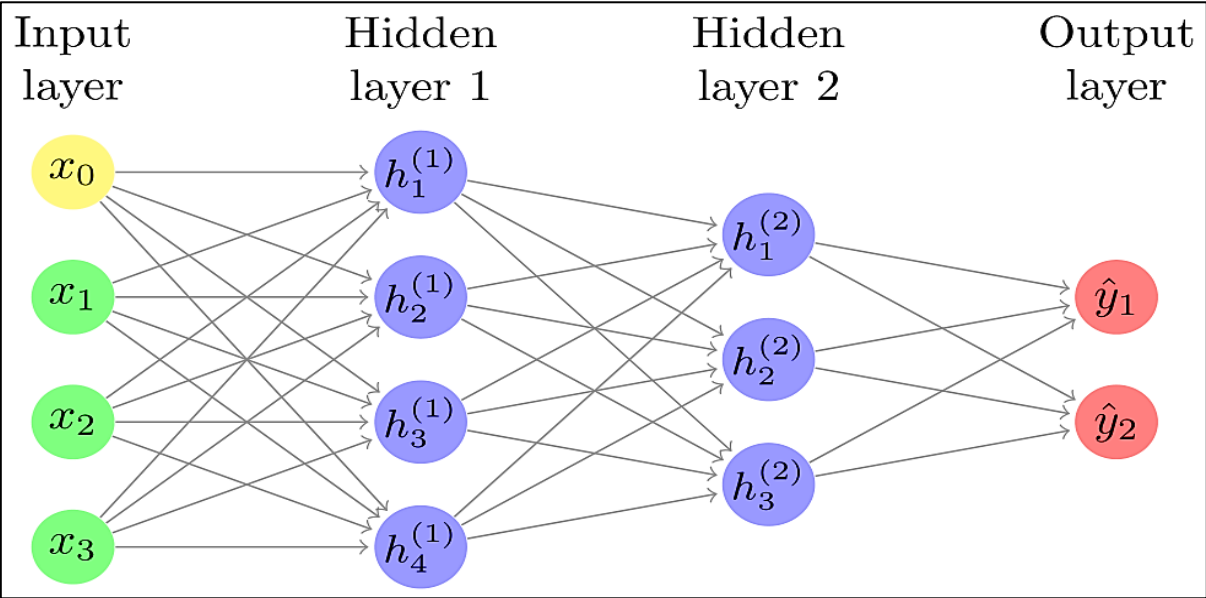


Figure 2.8: Convolutional neural network[91].

2.5 SUMMARY AND IMPLICATIONS

The 5G system has made tremendous progress in the field of communications as it provides high speeds of data transmission as well as a huge increase in bandwidth. The CA-NOMA technology has also contributed greatly to the development of the system, but it still faces some challenges, especially in the field of vehicle networks. Autonomous driving needs high accuracy and tremendous speed in transmitting data to avoid accidents and maintain safety. Also, artificial intelligence is a key factor in this development, especially with the increase in the volume of data that needs rapid processing. Artificial networks have an active role in accessing the required data smoothly and with high accuracy.

3 METHODOLOGY

3.1 INTRODUCTION

This chapter discusses how to obtain the data used in this thesis, as well as the algorithms and experiments used. The chapter begins with an explanation of a study on (CA-NOMA) technology, in which the architecture of the system is explained for the two users for simplicity. Where the architecture of the cache was explained, the method of saving files in it, and then determining the Optimal Power Allocation.

Then it was explained how to improve the system by artificial intelligence using two networks (MobileNetV2 and NasNETmobile).

At first, we defined the supposed system, then downloaded the data from the Kaggle site, then processed it using MATLAB, and got the results.

3.2 CACHING

Both V1 and V2 are assumed to contain a cache. The popularity of various types of user-requested data material varies. Since the law of (Zipf) ranks words by how often they appear [91],[92], it was believed that spreading these files would make them more well-known (Zipf). The probability of reusing a given word decreases as its position in the list increases.

$$F(r) = \frac{A}{r^\epsilon} \quad (3.1)$$

Where r represents the order of repeated words, $F(r)$ is the repeated incidence of r , (A) is a constant, and (ϵ) is the popularity coefficient. If we consider that the total number of files required is (F_{Total}) therefore, the popularity of the files is calculated as follows in eq (3.2):

$$G(f) = \frac{\frac{1}{f^\epsilon}}{\sum_{i=1}^{F_{total}} \frac{1}{i^\epsilon}} \quad (3.2)$$

With the aforementioned popularity profile, the ideal caching strategy will be to cache from the most popular file to the least popular one. [93].

3.3 OPTIMAL POWER ALLOCATION

Both V1 and V2 are assumed to have the files in their caches, and the data may be decrypted successfully if the received SINR is over a threshold. For the purpose of brevity, we fixed these thresholds and the noise variance (σ) to unity [94], [95]. Therefore, the probabilities of successful decoding in V1 and V2 are given by the following equations: (3.3) and (3.4):

$$P_{v1} = P\left\{\frac{\alpha P g_1^2}{\sigma_1^2}\right\} \quad (3.3)$$

$$P_{v2} = P\left\{\frac{(1-\alpha) P g_2^2}{\sigma_2^2}\right\} \quad (3.4)$$

where (α) presents Power Allocation Factor (PAF), (g_1) and (g_2) is the channel gains at V1 and V2, respectively.

3.4 PROPOSED SYSTEM

Transfer learning is used to use popular models that have previously been trained on massive amounts of data. Thus, the researcher may utilize and retrain these models by making adjustments to the last layers of a previously trained model's architecture and making use of our layers. After processing activities, we train 15 classes of MobileNetV2 and NasNETmobile models until we reach the necessary working accuracy. Figure 3.1 shows the working stages of all models. In this study, 5000 photos were used to recognize traffic signs put on the road using the MATLAB simulation tool. Data from the Kaggle website was utilized to train the two networks. This data contains different images of the road traffic signs, which vary in clarity to train the network on all weather conditions that may affect the clarity of the image on the road, as these images are very important for the self-driving of the vehicle because the vehicle needs information on the road continuously, which must be updated on an ongoing basis, which the base station provides this information.

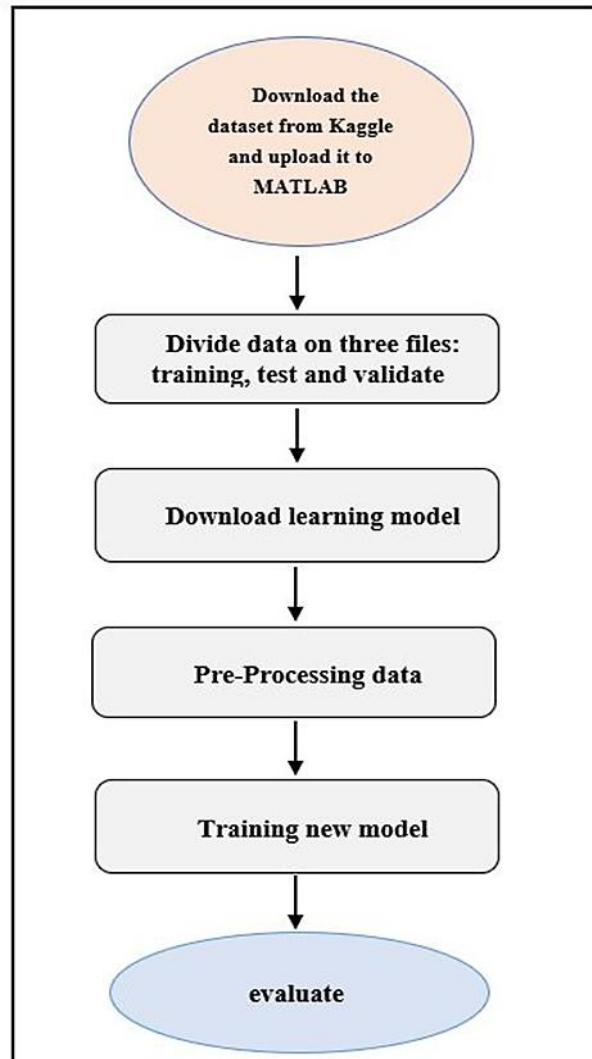


Figure 3.1: A proposed system

3.5 IMPORT DATA SET

The information was imported from Kaggle and entered into the *MATLAB*[®] program. after downloading and extracting the data. At this stage, we imported the data from the Kaggle website. The Kaggle website and the working application on the MATLAB program were used to divide the 5000-image dataset into 15 classes. The data was then divided into three sections: one for training, one for validation, and one for testing.

3.6 THE PRELIMINARY STAGE

In the course of this, we installed deep Network Designer in MATLAB, which includes a number of up-to-date learning modules for networks including MobileNetV2 and NasNETmobile. We increased the data we utilize in this study, which comprises 5,000 photos distributed across 15 categories. after installation, three folders were created for this data; one had training data, which made up 70% of the total, additionally, there is a folder named data validation that holds 20% of the data. 10% of the data is located in the last folder, Test Data, which is not equivalent in numbers. Each file in the collection has an image of a different kind of traffic light. To ensure the successful completion of the self-driving procedure, these signs feature numerous images with various clarity levels for training.

3.7 VALUATION STAGE OF THE MODEL

After achieving the necessary accuracy in train progress, which consists of two types of data: train and validate, the two models were assessed using test data. We use the Valuation function to assess the model, which displays the accuracy and loss for two networks, (MobileNetV2 and NasNETmobile).

4 RESULTS AND DISCUSSION

4.1 INTRODUCTION

This section explains how the NOMA technology and cache technology were integrated to make the fifth-generation network more efficient. Both the transmission power with and without cache, as well as the chance of successful decryption with and without cache, were included in the comparison.

The section also demonstrates the use of artificial intelligence in the development of CA-NOMA technology through the use of the CNN network, where a comparison was made between two types of this network (MobileNetV2) and (NasNETmobile) in identifying the traffic sign.

This chapter presents the results obtained from the comparison between NOMA technology and CA-NOMA technology, as well as the results obtained from traffic sign data using (MobileNetV2) and (NasNETmobile) networks.

4.2 EXPERIMENTAL RESULTS

The simulation findings that we provide here demonstrate how the cache coupled with NOMA contributed to an improvement in the functionality of the fifth-generation system. MATLAB is used to carry out each and every one of the simulations. The optimal distribution of power and a high chance of successful decoding are both objectives that must be sought. The simulation findings that we provide here demonstrate how the cache coupled with NOMA contributed to an improvement in the functionality of the fifth-generation system. For each and every simulation, MATLAB is the tool of choice.

In order to ensure that the information is sent to each and every subscriber, it is essential to work toward achieving an optimal power distribution and a high possibility of correctly decoding the data. The data in memory are organized according to a Zipf distribution, so the files that are used more often will be prioritized over the ones that are used less frequently. This ensures that the system runs as efficiently as possible. The results of a comparison between the efficiency of

the network with and without a cache are shown in Figure 4.1 for a number of various values of the variable (ϵ).

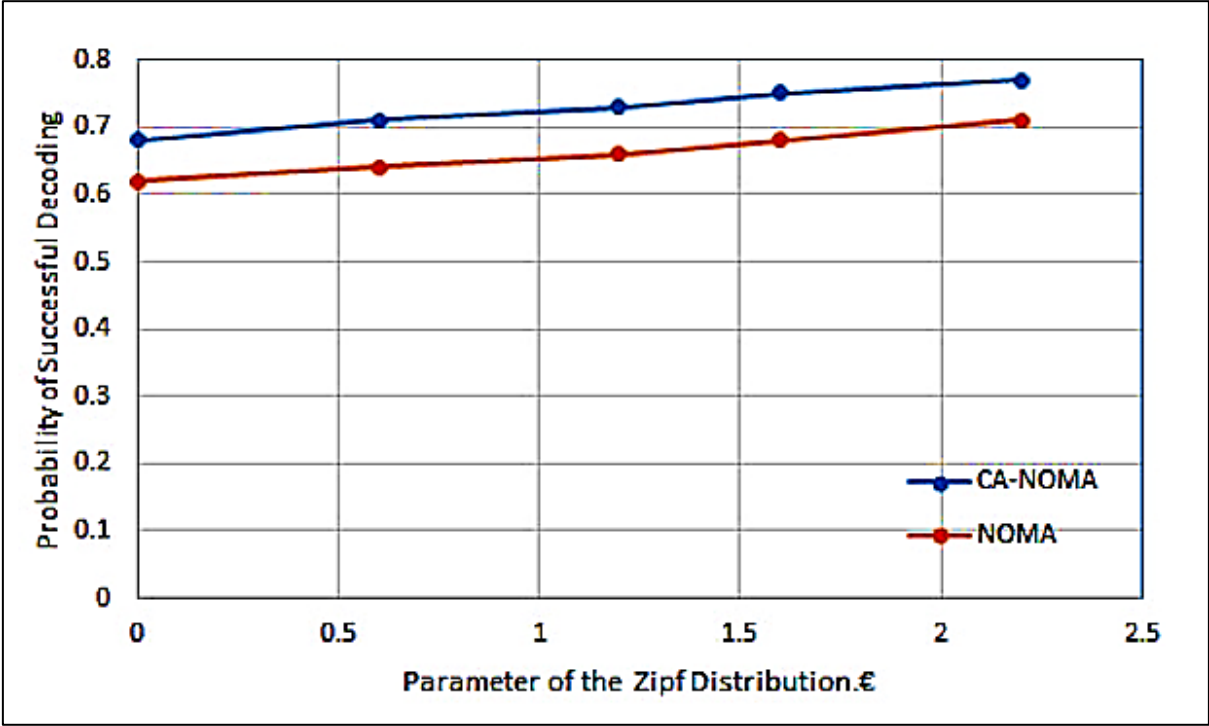


Figure 4.1: Analyzing the differences in performance between CA-NOMA and NOMA networks for varying values of (ϵ).

This highlights how the cache in cars improves speed, since files requested by other users may be cached, and the composite increases as the cache capacity grows (CA-NOMA). We also show that the success rate of the decoding increases with the value of the parameter (ϵ), leading to faster responses and superior overall performance from the auto network. Figure 4.2 shows how, as transmission power grows, decryption success rates rise. The cache clearly increases the chance, showing that subscriber requests may be satisfied without contacting the base station and that a particular user's information can be used to prevent interference if it is retained in the cache of a close user and exchanged with him on the same bandwidth.

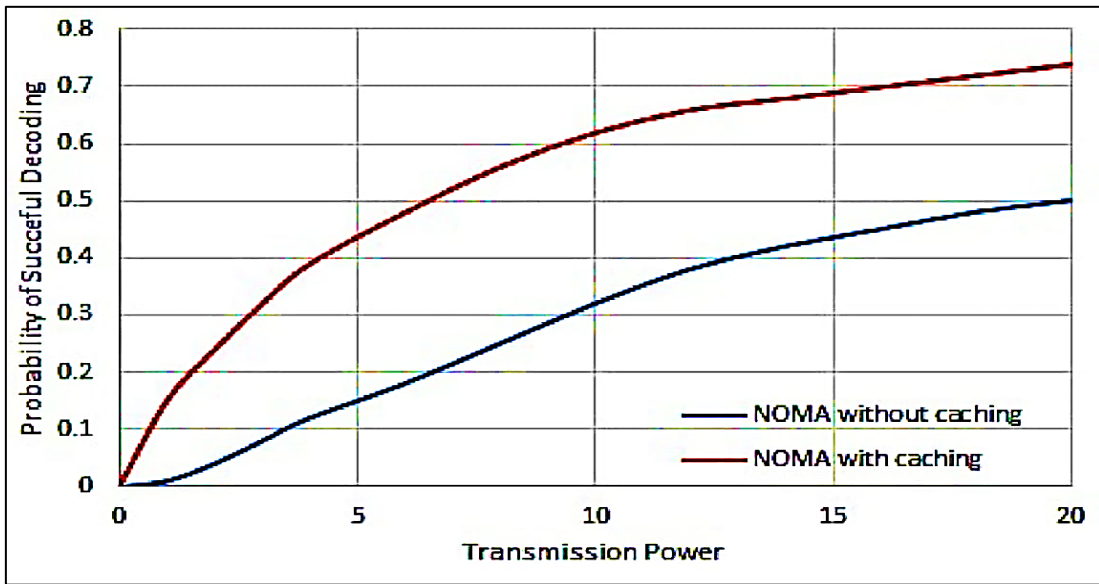


Figure 4.2: Possibility of decryption with enhanced transmission power, cache or not.

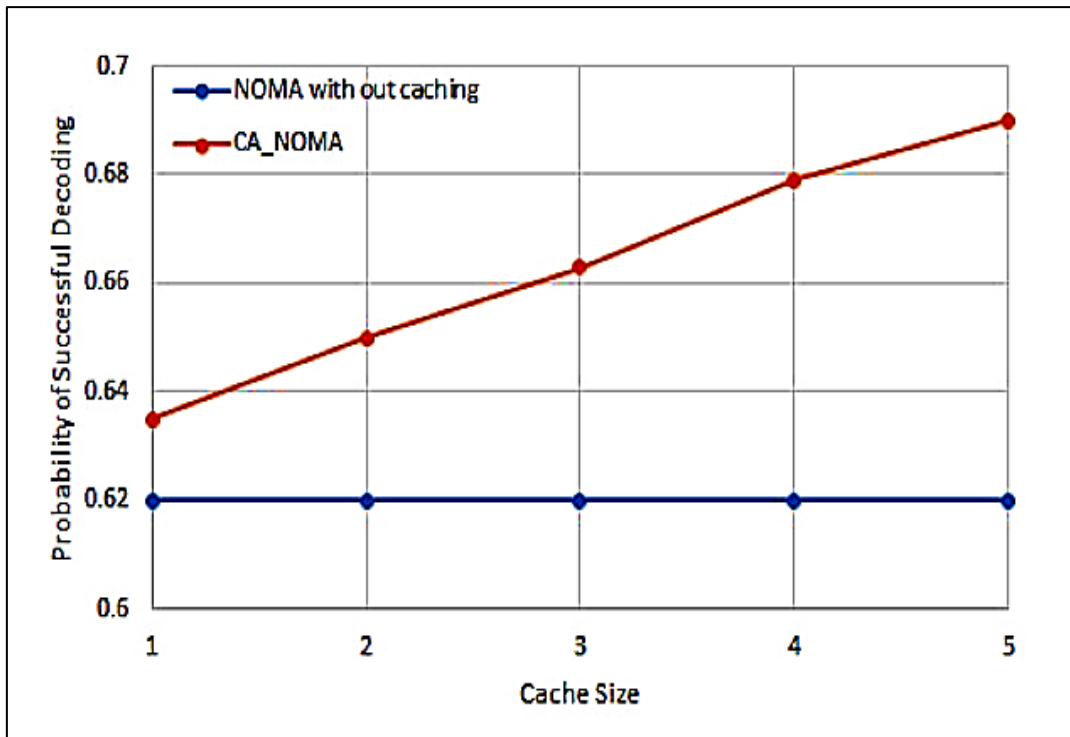


Figure 4.3: The impact of cache location in composites system performance compared to conventional NOMA, in terms of the likelihood of successful decoding.

Furthermore, we see that the performance of cache-added NOMA is identical to that of standard NOMA when the cache size is 0, or when there is no cache present in the automobiles. Cache sizes in both V1 and V2 are expected to grow in tandem with the likelihood that each vehicle will request its respective files. Figure 4.3 illustrates how optimizing cache location in moving vehicles may boost overall system performance.

4.3 EXPERIMENTAL RESULTS

The two models were trained using the specified training mechanism after processing the data of about 5000 images, which included 15 classes of traffic signs, and training to achieve the requisite precision in the job. To achieve the required accuracy, we trained 913 layers in the NasNETmobile, one of the newest convolutional neural network models. The MobileNetV2 model, which only required 154 layers to be trained, was determined to be the quickest in terms of training time, while NasNETmobile was found to be the most accurate. This is shown in Table 4.3 The evolution of MobileNetV2 and NasNETmobile, two training models are shown in Tables 4.1 and 4.2.

Table 4.1: Explain the training of MobileNetV2

	Train-Accuracy	Val-Accuracy	Train-loss	Val-loss
Epoch1	5.00%	15.70%	3.0857	2.9291
Epoch1	80.00%	52.97%	0.8561	1.4409
Epoch1	75.00%	74.22%	0.8450	0.8031
Epoch1	90.00%	77.58%	0.2008	0.3589
Epoch1	90.00%	88.44%	0.4795	0.3567
Epoch2	95.00%	91.54%	0.1297	0.1202
Epoch2	100.00%	91.86%	0.0839	0.0811
Epoch2	95.00%	96.58%	0.0654	0.0646
Epoch2	95.00%	94.64%	0.2744	0.1101
Epoch2	90.00%	87.21%	0.1610	0.0642
Epoch3	100.00%	94.38%	0.0122	0.0400
Epoch3	90.00%	94.90%	0.0668	0.0418
Epoch3	95.00%	96.64%	0.0566	0.0703
Epoch3	100.00%	97.55%	0.0058	0.0689
Epoch3	100.00%	97.22%	0.0253	0.0693
Epoch4	95.00%	97.80%	0.0014	0.0603
Epoch4	100.00%	97.87%	0.0002	0.0644
Epoch4	100.00%	97.87%	0.0007	0.0817

Table 4.1. explain the training of MobileNetV2. “tables continued”

Epoch4	100.00%	97.87%	0.0006	0.0720
Epoch4	100.00%	98.26%	0.0005	0.0724
Epoch5	100.00%	98.39%	0.0002	0.0445
Epoch5	100.00%	98.45%	0.0001	0.0520
Epoch5	100.00%	98.90%	5.2767e-05	0.0610
Epoch5	100.00%	98.64%	2.9324e-05	0.0658
Epoch5	100.00%	98.64%	2.9324e-05	0.0523

Table 4.2: Explain the training of NasNETmobile

	Train-Accuracy	Val-Accuracy	Train-loss	Val-loss
Epoch1	5.00%	15.70%	3.0857	2.8292
Epoch1	75.00%	61.97%	0.8571	1.3408
Epoch1	80.00%	75.22%	0.8461	0.7032
Epoch1	90.00%	78.58%	0.2007	0.2588
Epoch1	95.00%	89.55%	0.3790	0.2565
Epoch2	95.00%	92.30%	0.2296	0.1201
Epoch2	100.00%	92.56%	0.0725	0.0721
Epoch2	95.00%	95.57%	0.0525	0.0564
Epoch2	95.00%	94.63%	0.2433	0.1102
Epoch2	90.00%	88.22%	0.1612	0.0541
Epoch3	100.00%	94.38%	0.0121	0.0391
Epoch3	95.00%	95.86%	0.0659	0.0392
Epoch3	95.00%	96.64%	0.0557	0.0681
Epoch3	100.00%	97.55%	0.0049	0.0687
Epoch3	100.00%	97.22%	0.0242	0.0643
Epoch4	95.00%	97.80%	0.0013	0.0603
Epoch4	100.00%	97.87%	0.0002	0.0642
Epoch4	100.00%	97.87%	0.0006	0.0816
Epoch4	100.00%	97.87%	0.0005	0.0711
Epoch4	100.00%	98.26%	0.0005	0.0710
Epoch5	100.00%	98.39%	0.0003	0.0434
Epoch5	100.00%	99.45%	0.0001	0.0512
Epoch5	100.00%	99.50%	4.2767e-05	0.0592
Epoch5	100.00%	99.60%	1.9324e-05	0.0523
Epoch5	100.00%	99.60%	1.9324e-05	0.0523

Table 4.3: Compare two networks during the model valuation.

	MobileNetV2	NasNETmobile
Validation-Accuracy	98.71%	99.42%
Validation-loss	0.1317	0.1214

The data below depict the link between MobileNetV2 and NasNETmobile's accuracy and validity. Also, explain how each of the two training models is related to loss in train and validation as shown in the figures below.

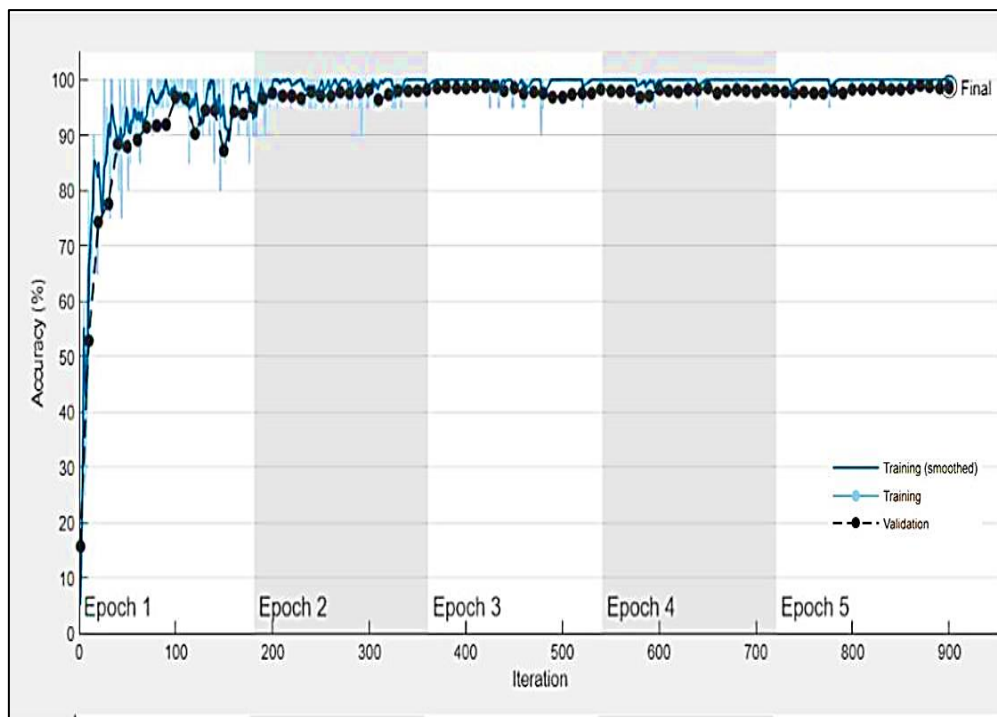


Figure 4.4: Compares validate accuracy and train of MobileNetV2.

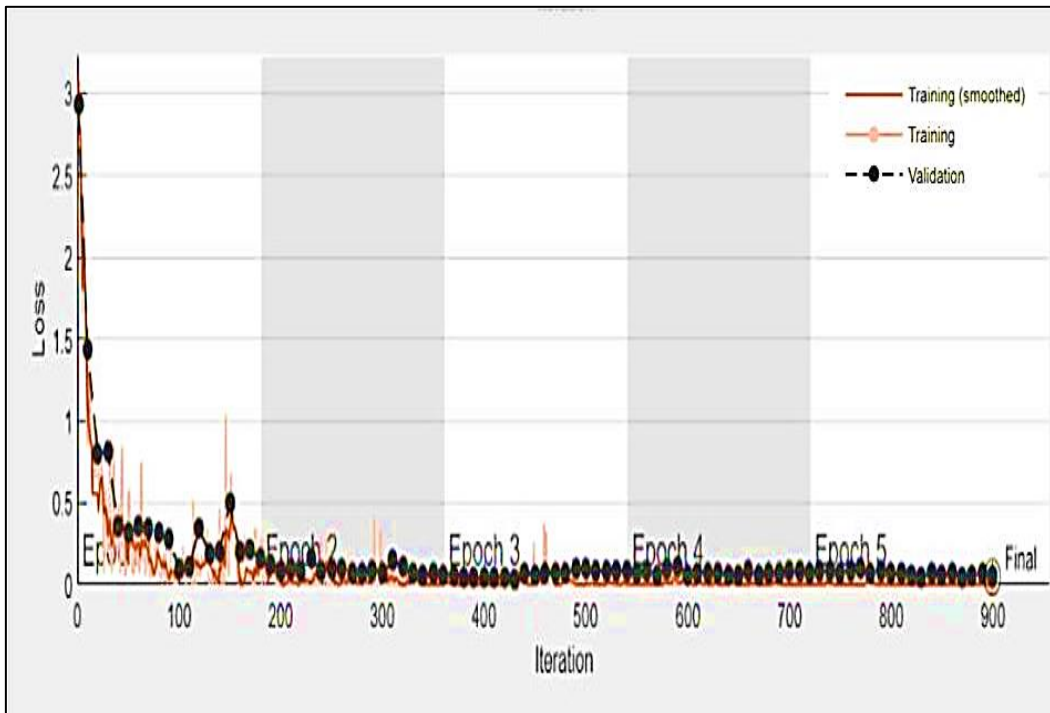


Figure 4.5: COMPARE between in MobileNetV2.

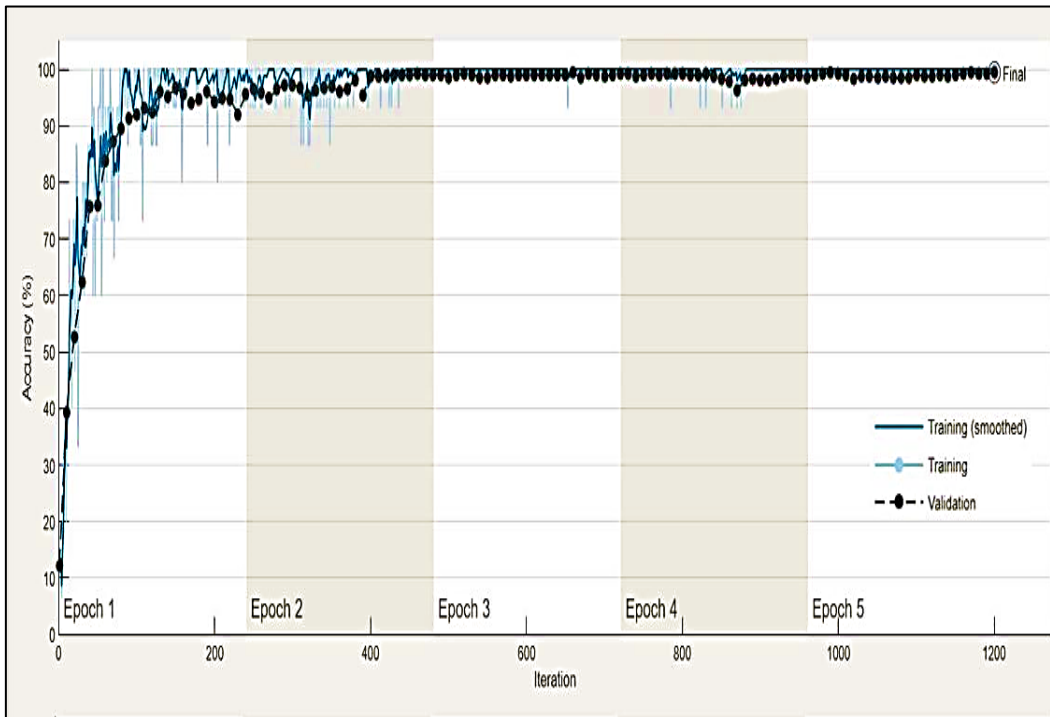


Figure 4.6: Compares validate accuracy and train of NasNETmobile.

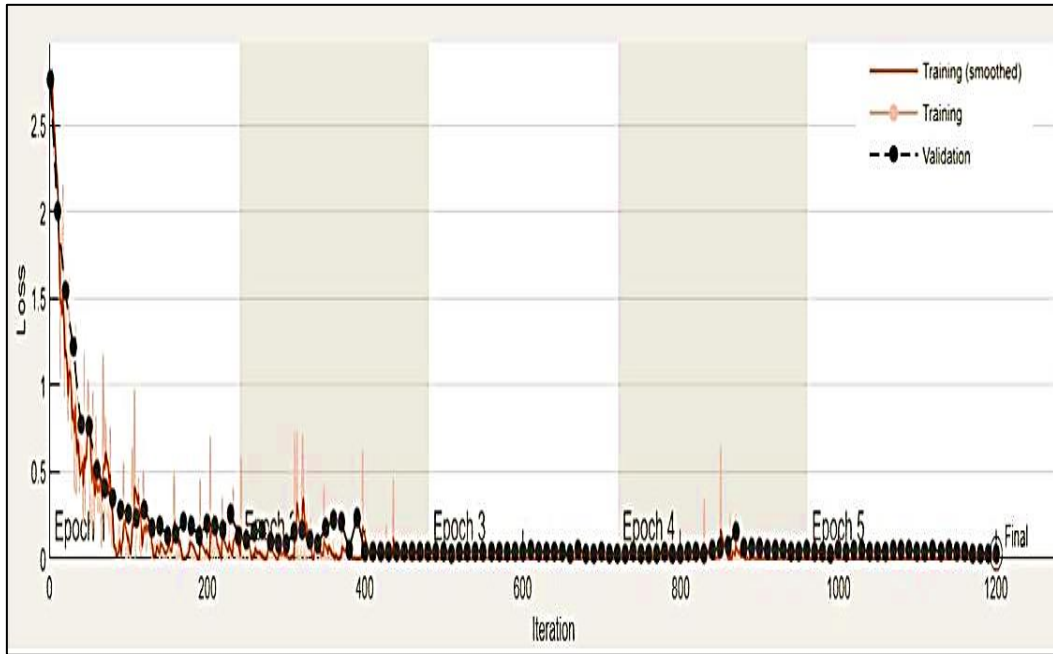


Figure 4.7: Compare between loss in NasNETmobile.

5 CONCLUSION

This CA-NOMA is a possible huge strategy for enhancing the functionality of 5G vehicle networks, especially in high-traffic conditions. This strategy is proposed as one of the primary strategies that may be used to improve the performance of 5G vehicle networks. The findings of the research illustrate how this cutting-edge technology increases the effectiveness of data transfer by allowing subscribers to access the caches of neighboring subscribers without the user's knowledge or agreement. The major objective is to improve the quality of the service provided to clients by improving the possibility that those customers will get the necessary signals. It was made abundantly clear that NOMA has a number of benefits over OMA, including those advantages' roles in the growth of the amount of data sent. It was also shown that employing cache content distribution based on popularity effectively helps to raise spectrum efficiency. This was demonstrated by the fact that the deployment of a cache in automobiles improved system performance in comparison to when the automobiles did not have a cache. Assuming that it is feasible to do so, the advantage of using this method might be extended by attempting to enhance the flexibility with which it can access the necessary data. For instance, this could be accomplished by dividing cache files into pieces. In-car file distribution also requires work to be invested in the development of a system for priority selection.

Throughout the course of this research, MATLAB software was used to instruct the MobileNetV2 and NasNETmobile models. Following the training, the models were compared to one another using the data from the training as well as the degree of accuracy that was attained by each network. According to the results of this experiment, MobileNetV2 and NasNETmobile may sometimes achieve accuracy levels that are equivalent to one another. This is the case despite the fact that NasNETmobile is more intelligent and can manage more photos and categories than MobileNetV2. Even though the conclusions that were discussed above are specific to this dataset, they could be relevant to other big datasets, and more studies might corroborate the influence of layer adjustment in order to achieve peak performance. It's likely that in the future, work in this area will be done utilizing block-wise fine-tuning rather than layer-wise fine-tuning. However, this is only a possibility at this point. In order to make the

process of grasping the findings of this study easier, it is required to carry out research into specific iterations of these structures.

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