IMPROVING MOBILE NETWORK PERFORMANCE WITH AI-POWERED CALL ADMISSION CONTROL (CAC)

A Thesis

Submitted towards the Requirements for the Award of Degree of

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IN

COMPUTER SCIENCE AND APPLICATION

Under the Faculty of Computer Science and Application

Submitted By

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This Thesis is dedicated to

my parents, my brother,

&

my beloved husband

whose unwavering support, blessings, and love

have been the foundation of my journey.

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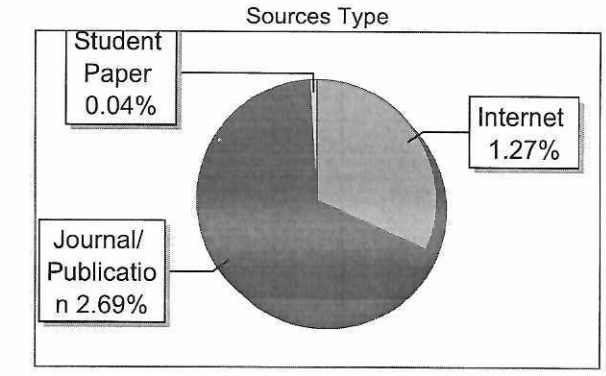
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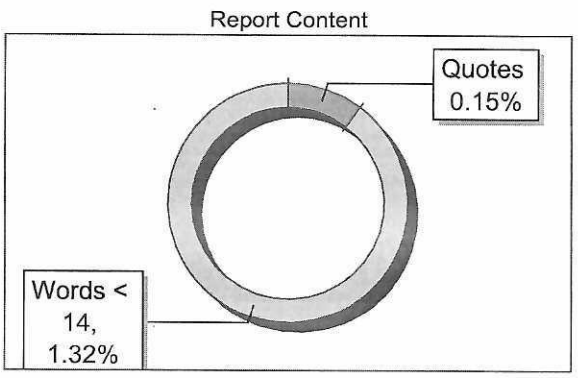
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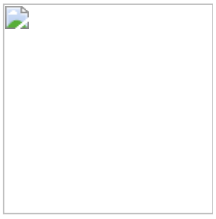
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LIST OF ABBREVIATIONS

S.No	Abb.	FullForm
1	CAC	Call Admission Control
2	CDMA	Code Division Multiple Access
3	DECT	Digital Enhanced Cordless Telephone
4	eMBB	enhanced mobile broadband
5	ETSI	European Telecommunications Standards Institute
6	FCC	Federal Communications Commission
7	FPLMTS	Future Public Land Mobile Telecommunication Systems
8	FWA	Fixed Wireless Access
9	IEEE	Institute of Electrical and Electronics Engineers
10	LTE	Long Term Evolution
11	MU	Mobile Users
12	QoS	Quality of Service
13	MSC	Mobile Switching Center
14	LU	Location Update
15	AP	Access Point
16	EBP-NN	Error Backpropagation Neural Network
17	CDP	Call Dropping Probability
18	HNN	Hopfield Neural Network

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ABSTRACT

Modern methods to improve network performance are required due to the exponential growth in user demand and the fast development of mobile networks. Although they do their job to a certain degree, traditional Call Admission Control (CAC) systems often fail to keep up with the intricate and ever-changing demands of today's mobile networks. In order to increase network performance, guarantee optimum resource allocation, and boost quality of service (QoS) for customers, this thesis investigates how Artificial Intelligence (AI) may be integrated into CAC.

Using AI methods such as Artificial Neural Networks (ANNs), Fuzzy Logic (FLs), and Genetic Algorithms (GAs), this thesis primarily investigates Call Admission Control (CAC) systems in mobile multimedia networks. Utilizing ANN and FL, new CAC methods for mobile networks have been devised, outperforming the old ones in terms of resource consumption, call dropping probability (CDP), quality of service (QoS), and call blocking probability (CBP). In order to provide mobile users in mobile multimedia networks with continuous QoS, the primary goals of the CAC scheme are to decrease CBP and CDP while maximizing resource usage via the employment of ANN and FL. In order to determine the user's mobility in a wireless environment, Error Back-propagation Neural Networks (EBP-NN) are used. Finding the mobility of both random and non-random MUs using their historical data is made much easier using EBP-NN, a multilayer feedforward supervised network. The queuing model is used to estimate and allocate resources based on mobility information. By providing a high throughput with a low number of handoffs, simulation outperforms other methods, significantly lowering CDP and CBP. Additionally, a channel allocation model based on Hopfield Neural Networks (HNNs) has been suggested for mobile multimedia networks to make effective use of bandwidth. Channels for new aAZAC) has been created. In terms of efficient use of resources and minimal CBP and CDP, the experimental findings show that the NFCAC Model is the best method.

Building an AI-driven CAC model that uses machine learning algorithms to forecast network circumstances and make smart admissions choices is the main goal of this project. The suggested model intends to predict resource availability, network traffic, and user movement patterns by combining real-time and historical data. By lowering

the likelihood of call dropouts and blocking and allowing for more precise and efficient resource management, this predictive capability greatly improves the user experience.

Computing overhead, data privacy, and integration with current network infrastructure are some of the issues that the thesis discusses in relation to the implementation of AI on mobile networks. The practical practicality of the AI-powered CAC model is ensured by proposing strategies to overcome these problems. To sum up, this thesis lays forth a thorough strategy for improving mobile network performance using CAC driven by AI. The results demonstrate that AI has the ability to completely change the way networks are managed, providing a strong answer to the growing problems with mobile networks. By outlining best practices for intelligent CAC system deployment, this study advances the state of the art and paves the way for future mobile networks that are both more robust and more efficient.

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

In the mobile communications industry, which is always changing and developing at a quick pace, ensuring that the network is performing at its best continues to be crucial concern. Because of growth of high-bandwidth apps, IoT devices, and smartphones, there has been an exponential increase in demand for mobile network services that are dependable and efficient. It is necessary for the underlying infrastructure of mobile networks, which consists of a complex web of base stations, antennas, and backhaul networks, to be-able to deal with the ever-increasing demand while simultaneously preserving quality of service (QoS) & quality of experience (QoE) for users. A technique known as Call Admission Control (CAC) is considered as important processes for managing network resources and ensuring smooth functioning. CAC algorithms have traditionally been rule-based, meaning that they have relied on predetermined thresholds and criteria to make choices on whether or not to accept incoming call requests rather than rejecting them. However, with advent of Artificial Intelligence (AI), in particular methods for machine and deep learning (ML and DL), there has been a substantial paradigm change in the manner in which CAC is implemented, which promises improved performance and efficiency in mobile networks.

In order to create judgments that are both better informed and more adaptable, artificial intelligence-powered call admission control uses the predictive capabilities of machine learning. Artificial intelligence algorithms forecast network congestion, user movement patterns, and even possible malfunctions by evaluating massive volumes of data in real time. This enables the algorithms to exercise more proactive and precise control over call admissions. This intelligence-driven strategy not only increases the efficiency of resource use, but it also improves the user-experience by minimizing call dropouts, enhancing quality of connections, and making certain that high-priority services get the required bandwidth. For fifth-generation (5G) and beyond networks, the incorporation of AI into CAC systems is of utmost importance. Ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), and enhanced mobile

broadband (eMBB) are some examples of the types of services that are included inside these advanced networks. These networks are distinguished by their heterogeneous nature, which encompasses a variety of services that have varying performance needs. Managing such a wide variety of services, it is necessary to possess a degree of agility and intelligence that is difficult to achieve with standard CAC processes. Systems that uses artificial intelligence constantly reacts to the different requirements of various services, which guarantees excellent performance across the board. [1]

Moreover, artificial intelligence-driven CAC plays significant role in tackling issues that are faced by network slicing, which is an essential component of 5G networks. With network slicing, it is possible to run many virtual networks on the same physical infrastructure, each of which may be customized to meet requirements of particular application or service. An artificial intelligence system is capable of properly managing a difficult job that involves ensuring that each slice has appropriate resources while avoiding interaction with other slices. The artificial intelligence-based CAC is able to distribute resources more effectively, so guaranteeing that each slice satisfies its service level agreements (SLAs). This is accomplished by continually learning and reacting to the circumstances of the network. CAC that is driven by AI has the capacity to improve network security and resilience, which is another important benefit its advantage. Artificial intelligence identifies possible security vulnerabilities by studying patterns and abnormalities in network data. It may then take preventative measures to minimize these threats. It is crucial to use-this preventative strategy in order-to protect against cyber-attacks and guarantee the dependability of mobile networks, which are becoming an increasingly important component of critical infrastructure in the modern connected world. However, use of AI in CAC systems also has economic repercussions, in addition to technological advantages that are already mentioned. When network efficiency is improved, operators are able to provide better services without having to make major investments in new infrastructure. This results in cost savings for the operators. Also, improved quality of service and quality of experience may result in increased customer satisfaction and retention, which is essential in the highly competitive market for telecommunications services. Making the switch to AI driven CAC has certain difficulties. For purpose of training the AI models, one of problems is need for enormous data of a high quality. There is substantial obstacle in the way of collecting, processing, and keeping this data in a manner that protects individuals' privacy. In addition, use of AI algorithms require the use of large-number of computational resources, which might

be a limiting issue, particularly in situations involving edge computing where resources are limited. Additionally, there is difficulty of integrating AI solutions with the network infrastructure that is-already in place, as well-as assuring compatibility between the equipment that is manufactured by various manufacturers.

Although there are certain-difficulties involved, the potential advantages of a CAC that is driven by AI are too large to ignore. Research and development in this field are making tremendous progress, with several studies confirming the viability of AI-based systems and the benefits they provide. One example is reinforcement learning, which is a subfield of machine learning. This subfield has shown significant potential in dynamically modifying CAC techniques depending on the network in real time. In a similar vein, deep learning algorithms-are being used successfully to forecast transportation trends and maximize the use of available resources.

A game-changing strategy for controlling the operation of mobile networks is represented by Call Admission Control that is driven by artificial intelligence. By utilizing the power of artificial intelligence, mobile network operators have the potential to attain levels of efficiency, flexibility, and dependability that never been seen before.

As mobile networks continue to develop and grow more complicated, AI ensuring that they operate at their highest possible level. The use of this technology is rather a need than just a choice for-operators who want to maintain their competitive edge and fulfill the ever-increasing requirements of users in this era of digital technology. In the future of mobile communications, intelligent, adaptable, and resilient networks will be the norm, and CAC that is driven by artificial intelligence will be an essential component of this fascinating journey.

1.2 HISTORY OF MOBILE COMMUNICATION NETWORKS

Radio communications may be traced back to the 19th century. In the year 1864, James Clerk Maxwell presented the Maxwell Equations, which are widely recognized as the equations for electromagnetic radiation. Telephones were first created by Alexander Graham Bell in year 1876. "Hertzian waves" were discovered by Heinrich Hertz in year 1887. These waves are now often referred to as radio waves. In the year 1896, Guillermo Marconi broadcast the very first radio transmission in the history of the planet. Over the course of the last half-century, there has been the potential for simplex radio communications, notably for radio reception for the general public, as well as duplex communication between the departments of law enforcement and inquiry. However, the duplex radio system was only effective for communications over small distances, and it was very unlikely that it could ever be considered for implementation on a big scale and on a worldwide scale. Over the last 15 years, wireless communications have undergone a transformation that is beyond comprehension. Analogue mobile phones were first widely used cellular mobile phones. Because of the heavy hardware that was necessary at the time, the first mobile phones were placed in automobiles. In 1978, shortly after availability of hand-held devices weighing more than-one kilogram, the Bell Telephone Company in United States developed the first cellular public network under the acronym AMPS, which stands for advanced mobile phone service. Additionally, the AMPS underwent a transformation and merged with the NMT (Nordic Mobile Telephone) of Germany. Subsequently, it was introduced in the United Kingdom under the name TACS (Total Access Communication Service). Beginning in the late 1980s and continuing up to the present day, development and implementation-of systems of the second generation took place. These were digital rather than analogue, and they were expected to provide the end user with improved voice quality. On the other hand, they were supposed to provide the operators with significant increases in terms of capacity per unit bandwidth.

Additionally, the capability of second-generation systems to roam is another benefit of these systems. Over the course of Europe, international roaming was made possible for very first time thanks to pan-European standard known as GSM (Global System for Mobile Communications). There are currently a great number of additional nations all around the globe that have implemented GSM. Digital AMPS (DAMPS) was created by United States of America via an evolutionary process inside its AMPS system. Code

Division Multiple Access (CDMA) is the foundation of the air interface that the US uses, and another standard called IS-95 is also in use. There was also the development of wireless standards for apps that used cordless telephones. These applications required users to have a personal "base" in their homes that was linked to a landline. CT2 was an early standard in both the United-Kingdom and Canada, and its digital second-generation equivalent, DECT (Digital Enhanced Cordless Telephone), was also an early standard. PACS-UB and IS-136 are the two cordless standards that are now in use in the United States of America. PACS-UB is mainly designed for use in a wireless PABX environment. Its many ports provide coverage zones which enables portable devices to swap connections between ports on a regular basis. PHS, which stands for "Personal Handy phone System," is a system that is comparable to the one used in Japan. The third area that is garnering a significant amount of attention is Fixed Wireless Access (FWA), which is also known as Wireless in the Local Loop (WLL).

This technology is developed to replace the cable that is used from the "last mile to the home." It is likely that FWA will be most successful in situations involving low-density communication, where the cost of cable is rather expensive, and in developing countries where the infrastructure for cabling is not yet in place. Global research now directed toward the development of third-generation systems, which are intended to provide complete access to multimedia content. Through the implementation of the so-called FPLMTS (Future Public Land Mobile Telecommunication Systems), it is possible to establish a global need. The Universal Mobile Telephone Standard (UMTS) is the name given to this project that is now being developed in Europe. In the United States of America, the technique described above is referred to as W-CDMA, which stands for wideband CDMA. It operates within a bandwidth of 5 MHz. CDMA2000 is the name of yet another 3G standard on the table in the United States. There has been a struggle about which standard to adhere to ever since they made their suggestion. [2]

A fascinating voyage of technical progress, the history of mobile communication is defined by innovations and transformational milestones that have significantly affected the manner in which people connect and engage with one each other. Mobile communication may be traced back to the early 20th century, when it began as crude wireless telegraphy and progressed to the sophisticated and pervasive cellular networks that are in use today. It is possible to trace the origins of mobile

communication back to the early 1900s, when radio technology was first developed. Significant contributions to wireless telegraphy were made by pioneers such as Guglielmo Marconi and Nikola Tesla. These achievements made it possible to transmit messages over large-distances without the need of physical wires. The foundation for future advancements in wireless communication was created by these first trials. The advent of mobile radio telephone systems in the 1940s marked the beginning of a crucial step toward development of mobile telephony. In-order to provide way of communication inside cars, these systems were largely used by public agencies, such as police departments and emergency services. It was clear that these early systems had number of drawbacks, including fact that they were cumbersome, had a restricted amount of range, and were restricted by the availability of radio frequencies. Bell Labs researchers, mainly Douglas H. Ring and W. Rae Young, came up with the notion of cellular networks in 1947, which was the next significant step forward in the development of the technology. They envisioned a network consisting of a network of tiny cells that were linked to one another and were each supplied by a stationary base station. This notion of cellular technology made it possible to reuse frequencies, which resulted in increasing the capacity of mobile networks. Despite this, the technology that could be-used to put this idea into-action was still in its infancy.

The creation of viable cellular systems did not-become possible until the 1960s and 1970s, when the essential improvements in computation and electronics were made available. Martin Cooper, a researcher at Motorola, made the first call using a prototype mobile phone in 1973. The connection was made using a portable mobile phone from Motorola. The modern age of mobile communication began with this momentous call, which marked the beginning of the day. It was in the early 1980s that the first generation of mobile networks, often known as 1G, was introduced. This generation was distinguished by analog transmission and restricted capacity. The switch to digital technology in the 1990s resulted in development of mobile networks that were of second generation, also known as 2G. Through the provision of communication that is both more effective and more secure, the Global System for Mobile Communications (GSM) standard brought about a revolution in the industry at its debut. Mobile internet was made possible with 2G networks, which made it provide services such as text message (SMS) and rudimentary data capabilities. Third- generation (3G) networks came into existence at the beginning of twenty-first

century. These networks, which brought greater data capacity and made it possible to provide more sophisticated services like video calling and mobile internet surfing, were launched. It was widely accepted that the Universal Mobile Telecommunications System (UMTS) standard was used, which resulted in improving the data transmission and the capacity of networks. There was a significant increase in mobile data services that were both quicker and more dependable because number of people using smartphones increases. Because of this need that, in latter part of the 2000s, fourth generation (4G) networks were developed. 4G networks, which were based on the technology known as Long Term Evolution (LTE), delivered significant gains in data rates and latency. These advancements made it possible to experience high-definition video streaming, real-time gaming, and other applications that need a lot of data.

At this point in time, the spread of fifth generation (5G) networks is the defining characteristic of the mobile communication generation. The fifth-generation (5G) technology, which is expected to be introduced somewhere between the late 2010s and the early 2020s, is a considerable advancement in terms of speed, capacity, and connection. With data speeds that are up to one-hundred times faster than those of 4G, ultra-low latency, and capacity to link large number of devices concurrently, 5G is poised to transform variety of sectors, from medical to autonomous cars. Additionally, the rollout of 5G networks is helping expansion of IoT, which is network that allows billions of objects to connect and interact with one another in a seamless manner.

The constant pursuit of innovation and improvement has been a driving force for development of mobile communication over its entire timeline. The use of cutting- edge technology, such as AI and ML, is contributing to the continued improvement of the capabilities and efficiency of mobile networks. use of these technologies is now taking place in variety of mobile communication-related domains, ranging from network administration to the improvement of user experience. Not only is the history of mobile communication a tale of technical advancement, but it is also tale of development of society. As a result of its ability to link people all over the world, make it possible to bridge distances, and enable new kinds of communication and engagement, mobile phones have become

an indispensable component of everyday life. In addition, development of mobile communication has significant repercussions for the economy, as it has-been a driving force behind the expansion of the telecoms sector and has given rise to new markets and possibilities. The history of mobile communication offers a basis for understanding the promise and problems-that lie ahead, which is important to keep in mind as we shift our focus to the future. Through the continuous development of fifth- generation (5G) networks and the research of sixth-generation (6G) technologies, it is anticipated that even more advanced capabilities will be brought about. These capabilities include immersive augmented reality (AR) and virtual reality (VR), as well as unparalleled levels of connection and automation. The history of mobile communication is a monument to the inventiveness of humans and the unrelenting quest of advancement. Beginning with the first trials with wireless telegraphy and continuing all the way up to the most advanced 5G networks of today, each milestone has built upon the accomplishments of the previous ones, propelling us into a future in which mobile communication will play-an important role in creating our environment. There-is no question that the lessons & innovations that been learned from this history will surely serve as a guide for the subsequent generation of technological advancements in mobile communication. [3]

1.3 CONCEPT OF MOBILE COMMUNICATION NETWORK

Since their origin, mobile networks have seen a remarkable change, moving from simple systems for voice communication to complex ecosystems that support a wide variety of applications and services that need a significant amount of data. There is a confluence of technology breakthroughs, legal frameworks, and customer demand that is at the core of this transformation. This convergence is profoundly transforming the landscape of mobile communications.

In the middle of the 20th century, when the idea of wireless telephony was only beginning to take form, mobile networks may be traced back to its beginnings. Early systems, such as Mobile Telephone Service (MTS), which was first established in United States in the 1940s, were largely used by public agencies and some sectors. These systems depended on analog radio technology. Not-only were these systems groundbreaking for their time, but they-were also characterized by restricted coverage,

cumbersome equipment, and exorbitant expenses, which made them unavailable to the common public.

It was in 1973 that Martin Cooper, an engineer at Motorola, made the first-handheld mobile phone-call using a prototype device. This was the moment that marked the beginning of the breakthrough. This momentous occasion initiated a paradigm shift toward personal, portable telephone, laying the groundwork for the present age of mobile communication and laying the framework for its subsequent development. The following commercialization of the first-generation (1G) analog cellular networks in the early 1980s heralded the beginning of a new era, which made it possible for users to have extensive access to mobile voice services. [4]

The introduction of digital technology in the 1990s played vital role in the acceleration of the development of mobile networks, which culminated in the introduction of second-generation (2G) telecommunications systems. The development of digital modulation methods, including as time-division multiple access (TDMA) and code-division multiple access (CDMA), resulted in considerable increases in spectral efficiency. These advancements made it possible to make more effective use of the radio spectrum and to create networks with a larger capacity. International standards such as the Global System for Mobile Communications (GSM) and the Interim Standard 95 (IS-95) were crucial in laying the framework for widespread adoption of mobile communication throughout the world. These standards made it easier for networks to communicate with one another and wander freely.

An age of widespread internet access and mobile data services was ushered in with advent of third-generation (3G) mobile networks, which came into-existence around the turn of the century. Utilizing data rates that were many times faster than those of its predecessors, 3G networks made it possible to use a broad variety of multimedia applications. These apps included online surfing, email, and instant messaging. The backbone of these networks was comprised of technologies such as the Universal Mobile Telecommunications System (UMTS) and Code Division Multiple Access 2000 (CDMA2000). These technologies provided unprecedented levels of data throughput and paved the ground for the revolution that was the mobile internet.

In the late 2000s, the exponential rise of mobile data traffic prompted the creation of fourth-generation (4G) Long-Term Evolution (LTE) networks. These networks were intended to fulfill the growing need for high-speed connection with low latency. LTE, with its all-IP architecture and improved radio access technologies, marked a big leap forward in the performance of mobile networks. It delivered data rates that were equivalent to those of fixed broadband connections. The introduction of 4G networks brought about a change in the digital world, which in turn fueled the expansion of applications that need a significant amount of bandwidth, such as cloud computing, online gaming, and video streaming.

Introduction of fifth-generation (5G) technology to mobile networks is most recent development in evolution of mobile networks. This technology promises to provide unparalleled levels of speed, capacity, and connection. Millimeter-wave (mmWave) spectrum, massive multiple-input multiple-output (MIMO), and beam forming are some of the sophisticated radio technologies that were used by 5G networks in order to achieve data transfer speeds that are up to one hundred-times faster than those of 4G LTE. There are a wide variety of applications that may be supported by 5G networks, including ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), and enhanced mobile broadband (eMBB). These applications are meant to support 5G networks beyond their sheer speed. Internet of Things (IoT), driverless cars, and augmented-reality (AR) and virtual reality (VR) are some examples of developing technologies that might benefit from this adaptability since it affords them new opportunities.

Mobile networks are dependent on the underlying infrastructure, which includes base stations, antennas, backhaul lines, and core network parts. This infrastructure is essential to the success of mobile networks. The deployment of these components is determined by a number of variables, including population density, geographical topography, regulatory constraints, and market demand. In order to meet high user density and demand for data traffic, urban locations often have dense deployments of small cells and macrocells. On the other hand, rural regions may depend on fewer, bigger cells to offer coverage across broad distances. Mobile network operators have a continuing challenge in optimizing network design and resource allocation. This

problem requires careful planning and investment to guarantee optimum performance and coverage.

In addition to technology improvements, regulatory laws and industry standards are also significant factor in development of mobile networks. The Federal Communications Commission (FCC) in the United States and the European Telecommunications Standards Institute (ETSI) are-examples of regulatory agencies that play an important part in process of assigning spectrum, enforcing licensing requirements, and assuring compliance with safety and security standards. Industry consortia and standards groups, such as the Institute of Electrical and Electronics Engineers (IEEE) and the Third Generation Partnership Project (3GPP), are responsible for the development and maintenance of technical specifications. These specifications are designed to encourage interoperability and innovation across the technology ecosystem.

On a worldwide scale, the spread of mobile networks has substantial socio-economic repercussions, since it is driving force behind digital inclusion, economic growth, and social change. Because it enables-access to information, services, and opportunities regardless of a person's geographic location or socioeconomic level, mobile communication has evolved into an instrument that is important for people, corporations, and governments alike. Mobile networks empower communities and bridge the digital gap, which in-turn fosters economic growth & social advancement. Mobile banking and remote healthcare delivery are just two-examples of the many ways mobile networks are helping in disaster relief and education.

In the future, mobile networks are expected to undergo significant development and innovation, which will be driven by new technologies like as artificial intelligence (AI), edge computing, and blockchain. An outlook that is optimistic is shown below. Through the dynamic adjustment of resource allocation, the prediction of traffic patterns, and the mitigation of network congestion in real time, optimization algorithms driven by artificial intelligence improves the efficiency and performance of networks. Edge computing makes it possible to do low-latency processing and storage at the network's edge, which opens up new-opportunities for applications that are-sensitive to latency, such as-autonomous cars and industrial automation. The blockchain technology provides decentralized and secure solutions for identity management, data

privacy, and transactional integrity. This technology is altering the way mobile networks handle identification, charging, and data sharing.[5]

The emergence of mobile networks is a monument to the inventiveness of humans, the invention of technology, and the joint effort of several sectors, including the government, academia, and industry. Mobile communication has gone a long way from its modest origins as analog voice systems. It has evolved into these high-speed, ultra-reliable networks that we use today, which has completely changed the way we live, work, and interact with the rest of world. The future of mobile networks comes with the potential for unlocking new possibilities, solving social concerns, and creating the digital environment of the future. This is especially true as we stand on the brink of the 5G era and beyond and as we move forward into the future.

There has been a significant shift in the landscape of communication and connection as result of mobile networks, which have provided wide range of advantages that are applicable to many different aspects of contemporary life. Their influence is pervasive, since they have an effect on personal communication, economic activity, healthcare, education, public safety, and the general growth of society. Mobile networks provide an unrivaled level of convenience and mobility, which is now at the forefront of these advantages. It is possible for-people to maintain connections with their family, friends,& coworkers at any-time and from nearly any place thanks to these devices. This continuous connectedness is an essential component of contemporary living, since it not only makes it easier to engage in social activities but also to participate in professional activities. Mobile networks make it possible for individuals to work remotely, enabling them to communicate and cooperate effectively regardless of where they are physically located. This is relevant in the professional world. In-recent years, this skill has become more important as result of the worldwide movement toward remote work, which has highlighted need of dependable mobile communication. As a result of flexibility that mobile networks provide, individuals are now able to handle professional activities while they are on the go, react to emails, participate in virtual meetings, and access essential documents from their smartphones or tablets. This has contributed to an-increase in productivity. The proliferation of mobile networks has resulted in the creation of vast number of new business prospects and markets, which has greatly contributed to the acceleration of economic development.

Mobile commerce, often known as m-commerce, has become more popular as result of this transition. Mobile networks make it possible-for customers to purchase online, make payments, and carry out many types of financial activities using their mobile devices in a smooth manner. In addition, mobile banking and payment technologies have transformed the financial industry by enabling means that are both easy and safe for managing accounts, moving money, and paying bills. The effect of this financial inclusion is especially significant in developing nations, which may lack the infrastructure necessary for conventional banking to function properly. Mobile networks assist bridge the gap between underprivileged groups and the formal sector by giving access to financial services via mobile platforms. This has effect of supporting economic empowerment and development. [6]

The use-of telemedicine and remote-patient monitoring has been made-possible by mobile networks, which have played a vital role in improvement of healthcare. Through use of mobile connection, telemedicine is able to provide remote consultations between patients and healthcare practitioners. This makes medical treatment more accessible, particularly in places that are underserved and rural. There is no longer a need for patients to travel significant distances in order to get diagnoses, medical advice, and follow-up treatment. Those folks who suffer from deadly diseases and need consistent monitoring and advice would benefit-tremendously from this approach. Patients also have ability to monitor their health metrics, get prescription reminders, and have access to variety of medical information via use of mobile health apps.

This gives patients ability to play an active part in the management of their own health. As result of their ability to assist the quick broadcast of vital information and the coordination of medical services in emergency circumstances, mobile networks have the potential to save lives. Mobile networks, which provide-support for online learning platforms and educational materials, have also-been a significant contributor to revolution in education. Learning has been democratized as result of the accessibility of educational information via mobile devices. This has-made it possible-for students from variety of backgrounds to have-access to excellent education. By use of video lectures, electronic books, and educational applications, mobile networks give learning experiences that are-both interactive and interesting to students. This has particular significance in locations that are geographically isolated or neglected, where the usual educational infrastructure may be missing. people are able to consistently update their skills and knowledge in a job market that is always developing thanks to the availability

of online courses, webinars, and training programs that are to be made available over mobile networks. This makes it possible for people to engage in lifetime learning and professional development. use of mobile networks allowed significant improvements in both public safety and emergency response. The capacity to rapidly distribute information during times of emergency is absolutely necessary for the purpose of coordinating response operations and protecting the safety of the general population. In the case of natural disasters, accidents, or other types of crises, mobile networks make it possible to quickly disseminate alerts and warnings to the general populace within the community. People may be informed of the essential precautions and evacuation procedures via this real-time communication, which can assist reduce the effect of catastrophes of this kind. Furthermore, mobile networks enhance the operations of emergency services by supplying dependable communication channels used for the purposes of coordination and dispatching procedures.

For instance, the first responders, are able to utilize mobile devices to get access to vital information, communicate with other responders, and rapidly route to the sites of incidents. In addition, mobile networks are an essential component in the process of bridging the digital divide, increasing social inclusion, and boosting digital literacy. Mobile networks contribute to the reduction of disparities in access to information and services by facilitating broad access to information and communication technologies (ICTs). Access to government services, participation in social and political activities, and participation in the digital economy-are all made possible by this connectedness, which gives people and communities ability to participate in these activities. By facilitating the production and distribution of user-generated content, establishing social ties, & promoting cultural exchange, mobile networks also assist the development of social and communal relationships.

Enhanced transportation and logistics are two more areas-that may benefit from the implementation of mobile networks. Individuals are-able to travel in manner that is both more efficient and safer as result of proliferation of smartphone apps that

provide navigation, ride-hailing, and real-time traffic reports. The functioning of smart transportation systems, which are dependent on real-time data to optimize traffic flow, eliminate congestion, and enhance public transportation services, is made possible by mobile networks. Within the realm of logistics, mobile networks make it possible to monitor and control shipments, hence enhancing the effectiveness and dependability of supply chain operations. As a result of offering access to weather predictions, market pricing, and agricultural best practices, mobile networks have proved to be very-useful tools for-farmers in the agricultural industry.

With this-knowledge, farmers will be-able to make more educated choices on crop management, which-will ultimately lead to increased productivity and sustainability. In addition, mobile networks make it easier to operate technology that are used in precision agriculture. These technologies take use of sensors and data analytics in order to improve agricultural methods. In addition, mobile networks provide a contribution to the preservation of the environment by facilitating the implementation of energy management systems and smart grid technology. For the purpose of optimizing energy usage, integrating renewable energy sources, and lowering carbon emissions, these systems depend on data that is collected in real time. The monitoring and management of energy systems may be made possible via mobile networks, which in turn improves the systems' efficiency and resilience.

The breadth and size of the advantages that mobile networks provide are anticipated to increase even more as they-continue to undergo development, beginning with introduction of fifth-generation (5G) technology and continuing beyond that. The Internet of-Things (IoT), autonomous cars, smart cities, & sophisticated applications such as augmented-reality (AR) & virtual-reality (VR) are all expected to benefit-from expansion of 5G-networks, which are-expected to bring faster speeds, reduced-latency, and larger capacity. New-opportunities for innovation, economic growth, & social progression will become available as result of these new developments.

1.4 CHANNEL ALLOCATION SCHEMES

1.4.1 CONCEPT OF CHANNEL ALLOCATION

An essential idea in communication systems, channel allocation describes how available communication channels are distributed to different users or devices in-order to make the most efficient use of limited frequency spectrum resources, & it is especially important in wireless networks. By allocating channels efficiently, we may optimize throughput, minimize interference, and improve the network's overall performance.

One limited resource in wireless communication is radio frequency spectrum. In order for-each user or device to send data, they need access to certain piece of the spectrum. The difficulty comes from having to distribute these channels in a way that keeps each user's quality of service (QoS) needs met while avoiding interference from neighboring channels (which are close by) and co-channels (which are on the same frequency).

You may classify channel allocation schemes as either fixed or dynamic, depending on your preference. Each cell or user is permanently assigned certain channels using fixed channel allocation (FCA). This approach is straightforward and quick to execute, but it may not be the most efficient, particularly when dealing with unpredictable traffic situations. The capacity of the spectrum is squandered if one channel is overused, while other channels may become overcrowded.

In contrast, channels are assigned using dynamic channel allocation (DCA) according to the demand and present state of the network. Adapting to changes in user distribution and traffic load, this strategy is more adaptable and efficient. As users relocate or their communication requirements evolve, they may have their temporary channels changed in DCA. The network's load is distributed more evenly and congestion and interference are less likely to occur as result of this dynamic method.

Utilizing frequency reuse, an approach that partitions the accessible spectrum into several bands and then allocates these bands to cells in a manner that minimizes interference, is one sophisticated strategy within DCA. As an example, a cellular network's total capacity may be greatly increased by allowing-cells that are not near to each other to utilize same frequency range.

Using algorithms and computational models to improve channel distribution is another

significant topic in channel allocation. One way to reduce interference between cells is to utilize algorithms like the graph coloring method to make sure that neighboring cells don't use the same frequency. Alternative methods include optimization models that reallocate channels dynamically in-response to user mobility, traffic patterns, & quality of service needs, among other things.

5G and the IoT are two examples of new technologies that rely-heavily on channel allocation. From autonomous cars' need for low-latency communications to video streaming's high-bandwidth demands, 5G networks' allocation must handle a large number of devices with varying needs. For effective spectrum management and dynamic channel allocation, methods like beamforming and large MIMO-(Multiple Input Multiple Output) are used.

1.4.2 SCHEMES OF CHANNEL ALLOCATION

Fixed channel allocation (FCA), dynamic channel allocation (DCA), hybrid channel allocation (HCA), and flexible channel allocation (FlCA) are the four primary categories that may be used to classify the various channel allocation techniques. [7]

A. Fixed Channel Allocation

Purpose of these schemes is-to provide each cell with a set of channels that are permanently allocated to it for its exclusive usage. In this case, the co-channel reuse requirement ensures that there is clear and unambiguous connection between every channel and every-cell. In other words, the spectrum is split into sets, and the minimum number of channel sets (N) necessary to provide the whole coverage area is connected to reuse distance. Total number of channels that are accessible is also known as the spectrum. In situations when there is consistent traffic, the same number of channels is assigned to each cell, and this number does not change over course of time. In-terms of channel allocation, this is the best possible method. However, in the event that the traffic is not consistent, it is possible that separate cells will be assigned a different set of channels. Cells with a greater traffic load have to find way to make advantage of free channels that are available in cells with a lower traffic load. For proper implement the channel allocation method, we need to include call blockage likelihood as a criteria. The complexity of this method increases greatly because of relationship between the channels and the chance of call blockage is a complicated function. Investigations have been-conducted on algorithms that allocate channels among the cells in-accordance with

the traffic load present in each cell. As-an example, a non-uniform compact channel allocation mechanism is given in the discussion. It is shown via simulations that the method offers a higher call-blockage likelihood inside the system with its implementation.

Channel Borrowing Techniques in FCA

This means that FCA, which is severely loaded cell, will borrow channels from surrounding cells, provided that there is no interference with any communication sessions that are already in progress. To put it another way, the tactics that are referred to-as channel borrowing are used by high traffic cells in order-to borrow channels belonging to low traffic cells. For the purpose of borrowing channels, there are two ways available: temporary channel borrowing and static channel borrowing. High-traffic cells that borrow channels temporarily return them when the call has been finished. This practice is known as temporary channel borrowing. Channels are not equally allocated across cells in process of static channel borrowing. This is-done in accordance with the data of the traffic that is available, and the channels are modified in way that is predictive.

A summary of many approaches that may be-used to choose free channels from a heavily loaded cell for the purpose of borrowing by another cell can be found in. These strategies either make all channels available for borrowing, which is referred to as simple borrowing schemes, or they divide the channels between those-that are accessible for borrowing and those that are not-accessible for borrowing, which is referred to-as hybrid borrowing schemes. Under conditions of mild or moderate traffic pressures, it has been-found that simple borrowing systems perform better. An analysis of the quantitative differences between several of these methods is presented in. Channel borrowing systems need an increase in the complexity of the computations involved and result in frequent channel changes. Further, they could have an-effect on handoff techniques. In cellular networks, FCA methods are-unable to achieve high channel efficiency when-dealing with short-term fluctuations in both the temporal and spatial characteristics of traffic.

B. Dynamic Channel Allocation

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C. Hybrid Channel Allocation (HCA)

The channel allocation optimization is achieved by use of a combination of FCA and DCA techniques in this system. It-is claimed that these kinds of schemes are nothing but the combination of FCA and DCA, in which -total number of channels-accessible for services is separated-into sets that are either fixed or constantly changing. As is the

case with FCA schemes, the fixed set is comprised of principal channels that are only designated for use of a certain cell. On other hand, the major channels are the ones that are more often used in the cells. Because-of this, the second set of channels in system is shared by all the cells, which results in increased flexibility. A channel from the dynamic set is allocated to the cells using the DCA method when a communication session needs a channel in a cell that is already occupied by all main channels. The channel that was assigned to the cells is then returned to the dynamic set shortly after the communication session is over.

D. Flexible Channel Allocation (FlCA)

Within the framework of the flexible channel assignment method, the available channels are-partitioned into two distinct sets: the fixed set and the flexible set. The channels in the fixed sets are allocated to the cells in accordance with the FCA scheme, which are enough for light traffic load. On other hand, the flexible channels are assigned to cells whose channels have become insufficient as result of growing traffic load, either in a scheduled or predictive way.

1.5 CALL ADMISSION CONTROL SCHEMES

1.5.1 CONCEPT

Call Admission Control, often known as CAC, is an essential mechanism in mobile networks. Its primary function is to regulate the admittance of new calls and data sessions, both of which are necessary for guaranteeing optimal resource allocation and preserving Quality of Service (QoS). The major goal of the CAC is to determine whether to accept a new call request depending on the existing circumstances of network and availability of the resources. This helps to reduce congestion on the network and ensures that ongoing calls are not negatively impacted. Many different CAC schemes have been established over course of time, each with its own-unique set of procedures and benefits. These schemes are a reflection of the technical developments that have occurred and the ever-changing needs of mobile-communication networks.

Fixed threshold policies were foundation of the original CAC programs, which were simple and reasonably basic. The call admission process was determined by these schemes, which are-sometimes referred to as static CAC. These schemes made use of

predetermined characteristics, such as number of current-calls or amount of resource use. If the load on network reached a specific level, then any additional-calls that were received would be declined. The static CAC systems had severe drawbacks, despite fact that they were easy to implement. They lacked flexibility and were often conservative, which resulted in wasteful usage of resources and inferior quality of service, particularly in network settings that were susceptible to dynamic changes. [8]

The implementation of dynamic CAC methods was done in-order to overcome these restrictions. Dynamic CAC adjusts to circumstances of the network in real time, allowing-for better informed judgments are made on the basis of availability-of resources and the anticipated demand in the future. ability of network to handle extra calls is evaluated by these-systems via the use of variety of measures, including signal-to-noise ratio (SNR), interference levels, and user movement patterns. By making admission choices that are more accurate and faster, dynamic CAC helps to enhance both resource utilization and quality of service.

Measurement-based systems was a key step forward in the development of CAC. Continuous monitoring of network performance metrics, including as call drop rates, call blocking rates, and handover success rates, is essential to the operation of these programs. It is possible for measurement-based CAC systems to dynamically alter admission criteria in order to maintain the target quality of service levels by assessing this data. To provide one example, if call drop rate is higher-than a certain threshold, the CAC algorithm may become more restricted in terms of accepting new calls. This would ensure that the quality of the calls that are already in progress is maintained at a satisfactory level. By using this strategy, the network's capacity to adjust to different traffic levels and user behaviors is considerably improved.

CAC systems have developed in-order to manage the complexity of multi-tiered architectures in context of heterogeneous networks, which are networks in which several kinds of cells (macro, micro, Pico, and femto) coexist. When operating in such situations, CAC is required to take into consideration a variety of aspects, including user density, cell coverage regions, and the differing capacity of various cell types. Schemes such as hybrid CAC have been created in- order to improve the

Efficiency-with which resources are managed throughout these several cells. The hybrid CAC incorporates different techniques, such as conserving resources for high-priority users or services while dynamically modifying to real-time traffic patterns. This allows the hybrid CAC to adapt to changing traffic patterns. Because of this, optimum resource allocation is ensured, and the overall performance of network is improved.

In addition, introduction of 4G LTE and the eventual development of 5G networks have further pushed the limits of CAC systems towards their limits. The idea of network slicing has been used in both 4G and 5G networks, which enables operators to establish several virtual networks on a single physical infrastructure. Each slice has the capability of being adapted to certain services, such as enhanced mobile-broadband (eMBB), ultra-reliable low-latency communications (URLLC), and-massive machine-type communications (mMTC). In a network environment that is sliced in this-way, the CAC is responsible for-ensuring that each slice satisfies its service level agreements (SLAs) while also effectively sharing the resources that are under the surface. Because of these needs, artificial intelligence (AI) & machine learning (ML) approaches have become integral. In order to optimize resource allocation, forecast congestion, and dynamically alter admission rules in-order to maintain quality-of service across all network slices, CAC schemes that are driven by AI make use of predictive analytics and real-time data processing strategies. Within the context of CAC, reinforcement learning (RL), which is subset of machine learning, has shown tremendous potential. This is accomplished by RL-based CAC schemes interacting with the network environment and getting feedback in the form of incentives or penalties. This allows the schemes to learn the best admission criteria. Over time, these schemes continue to improve their decision-making skills, which ultimately results in improved resource management and quality-of service capabilities. For instance, a CAC that is based-on RL may learn to anticipate periods of high traffic and alter admission criteria appropriately, so minimizing congestion and ensuring that network operates smoothly. use of game theory is yet another novel strategy that is utilized in CAC. CAC systems that are based on game theory represents the interactions between several users or network entities as if they were similar to a game, with each player attempting to maximize their own utility. Game-theoretic CAC is able to build strategies that balance the conflicting demands for network resources by evaluating these interactions. This ultimately leads to an equilibrium state that maximizes the

overall performance of the network. In decentralized networks, where numerous stakeholders with different goals utilize the same infrastructure, this technique is especially valuable since it allows for the sharing of diverse objectives.

The incorporation of artificial intelligence and machine learning into CAC schemes also tackles the difficulty of managing a wide variety of quality-of-service needs for various kinds of services. For example, video streaming-services need to have high bandwidth and a low latency, but voice conversations need to have constant quality and not have major delays. CAC systems-that are powered by AI are able to categorize various kinds of traffic and implement admission criteria that are specifically suited to meet the needs of each service. This guarantees that the essential services are provided with the resources they need while-simultaneously preserving the overall efficiency of the network. The capacity of the network to anticipate and react to user movement patterns is further improved by CAC systems that are driven by artificial intelligence. These schemes are able to predict handovers and pre-allocate resources in the target cells by assessing historical data and real-time user location information. This helps to reduce possibility of call dropouts occurring during transitions. Maintaining smooth connection is particularly important in high-mobility settings, such as when users are moving in automobiles. This predictive capacity is essential for performing this task.

It is expected that function of CAC will become even-more important as mobile networks continue to advance toward 6G and beyond. The next generation of networks is anticipated to be capable of supporting a wide variety of applications, ranging from virtual reality (VR) and augmented reality (AR) experiences that are completely immersive to smart cities and driverless cars. The demands that these applications will make on network resources will be unparalleled, and they will need CAC systems that are very flexible and intelligent. The primary objective of the research being conducted in this field is to build CAC algorithms of the next generation that are-capable of using modern-artificial intelligence methods, such as deep learning and edge computing, to manage resources in real time and guarantee optimum performance across a wide range of demanding use cases. Since it was first introduced, Call Admission Control (CAC) has undergone a substantial amount of development in order to accommodate the ever-shifting environment of mobile communication technology. CAC has undergone constant improvement in order to satisfy the ever-increasing and varied requirements

of current mobile networks. These improvements began with static threshold-based techniques and progressed to dynamic, measurement-based, and AI-powered systems. CAC's capacity to effectively manage resources, maintain quality of service, and support a diverse variety of services and applications all these significantly improved because of the incorporation of cutting-edge technology like as artificial intelligence, machine learning, and game theory. For mobile networks to be able to meet ever-increasing demands of digital era, in terms of both complexity and performance, it will-be necessary to design CAC schemes that are both intelligent and adaptable as we go forward into the future with 5G, 6G, and beyond.

1.5.2 SURVEY ON CAC SCHEMES

An-analysis of current CAC schemes is-presented in this-part. These schemes-are divided into-four categories: Bandwidth Reservation (BR), Bandwidth Degradation (BD), Bandwidth Reservation and Bandwidth Degradation (BR-BD), and Non-BR and Non-BD (NBR-NBD). Detailed discussion and analysis of these categories is presented as follows:

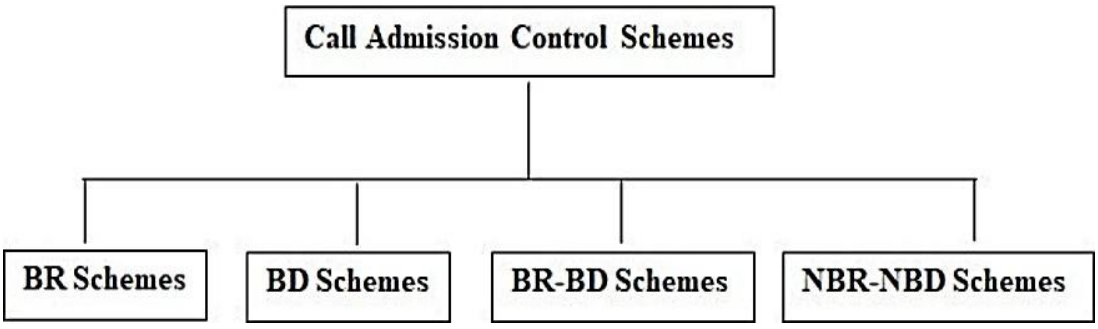


Figure 1. 1 CAC Schemes

Source: Secondary source taken from: https://www.researchgate.net/figure/Categorization-of-CAC-schemes_fig4_336924154

Bandwidth Reservation (BR) Schemes

The BR schemes divide up the available resources between Handoff Calls (HCs) and New Calls (NCs), with a certain proportion reserved for HCs. Here are the schemes that have been reviewed:

To make sure that the probability of a handoff call dropping is minimal, a Guard Channel (GC) method was suggested in. Handoff calls are allotted a certain amount of resources by the GC mechanism. If there are less resources available than the incoming call requires, the scheme will block the call. A handoff call will be lost, if there is no accessible channel. The HCDP goes down and the NCBP goes up because HCs are given more priority.

In order to reduce NCBP, we propose a method called Fractional Guard Channel (FGC) or Thinning Scheme-I. With the FGC system, HCs get a portion of the network's total resource while NCs and HCs split the rest. Assuming there is at-least one available channel, the system will allow NCs according to predetermined probability (which does not grow with number of occupied channels) and HCs without restriction. Reserving a set amount of resources that may-not be completely used reduces the NCBP but wastes network resources.

Another strategy that was suggested by to lessen NCBP is the Uniform Fractional Guard Channel (UFGC). An alternative to the FGC plan, the UFGC scheme sets aside a non-integral amount of resources for HCs. A constant probability that is unrelated to number of occupied channels and arrival rate used by the system to accept NCs, which is known as an acceptance probability. Because there aren't enough reserved resources, it lowers NCBP and HCDP when the arrival rate of traffic is low but raises both under high traffic.

To control the proliferation of NCs, the authors of put forth the New Call Bounding (NCB) approach. In order to protect funds designated for HCs, the NCB plan establishes a limit (the maximum number of NCs that may be accepted). If the threshold is not surpassed, the scheme admits an NC; nevertheless, HCs are only banned if all channels are in use. The quality of service of continuing calls is guaranteed as it reduces HCDP. Nevertheless, the NCBP is significantly increased by the system because of the threshold value, and network resources are wasted since the reserved resources could exceed the HC traffic.

An LFGC system was suggested in order to guarantee improved QoS. Based on channel occupancy, the LFGC method changes the number of reserved HC channels by a fraction of one. Two parameters are used by the scheme: the quantity of guard

channels (T) and the likelihood of NC acceptance (βl). In the beginning, T is set to 1, βl is set-to 0, and T is increased by 1 until the necessary quality of service is achieved. The technique improves QoS and reduces NCBP, but it raises HCDP since channel use is not taken into account.

For Multi-service OFDM Networks, we suggested a CAC with Resource Reservation mechanism to guarantee quality of ongoing calls. The scheme sets aside additional resources that any user accepted to the program may utilize during call holding. All active calls have their QoS improved by the system. The enhanced reservation approach, however, causes it to squander network resources.

Reducing excessive call blockage and wasting of network resources was the goal of proposing the queuing concept in. The concept sets aside certain channels for HCs and grants NC requests when there are enough leftover resources. Instead of incorrectly blocking NCs, it queues them instead, and when resources are low, it dumps HCs. In situations with high volumes of traffic, the strategy improves HCDP while decreasing NCBP.

To assure quality of service, a new advanced resource reservation-based CAC (AR-CAC) method was suggested in. The AR-CAC approach establishes threshold for each of three types of calls—advanced, HC, and new immediate—based on their relative importance. When all-available channels are busy, the scheme queues HCs and saves resources for future use by making advance calls. If there are several HCs in the queue, it serves them on a first-in, first-out (FIFO) basis, but it admits them if certain resources (sub-channels) are freed and their delay time-out has not reached. Any new immediate call will be accepted by the scheme if their combined resource requirements-are less than or equal to the new call threshold; otherwise, they will be refused. In order to distinguish between advance and immediate calls, it specifies a minimum start time. It also limits amount of advance calls by rejecting calls that exceed maximum book-ahead start time. The strategy improves QoS by reducing HCDP, but it wastes network resources by increasing NCBP and not using the resources allocated for advance calls to their full potential.

Suggested a Dynamic CAC (DCAC) and a Bandwidth Reservation CAC (BRCAC) to guarantee equitable distribution of resources during peak use times. Voice GBR, non-voice GBR, and non-GBR are the three service classifications that the BRCAC scheme assigns to incoming call requests. The technique adapts amount of allocated resources-for voice GBR calls in real-time according to the VoIP call traffic intensity. Using an outage probability for non-VoIP calls, the DCAC system gives priority to VoIP calls during busy hours. This likelihood is bandwidth and VoIP request arrival rate dependent. When there are sufficient-resources in network to accept all call requests, it is-set to zero. The quality of voice traffic is substantially enhanced by these techniques, which decrease HCDP. Unfortunately, the schemes' reliance on outage probabilities makes them unfair to non-voice calls and their disregard for channel quality leads to wasteful use of network resources.

To enhance the usage of resources, a Ring Based CAC (RCAC) Scheme was suggested in. In light of the RCAC's present mobility estimate, a certain amount of resources-are set aside for HCs. In the absence of free resources in the UE's Most Likely Cell-Time (MLCT), it rejects the call if the resources at that node are insufficient. A cluster of time units, the MLCT indicates the future visits of mobile UEs and the times and locations they are most likely to occur. To forecast user mobility, the RCAC scheme consults the mobile UE's MLCT to see if any free resources are-available. It improves the usage of network resources & decreases the HCDP. Unfortunately, the strategy is inefficient since it over reserves resources due to its mobility forecast being unclear.

An algorithm for CAC was suggested for high-speed vehicle communication networks with the aim of lowering NCBD and HCDP. For continuing calls and NCs, the plan sets aside funds. It takes into account both the resources needed to complete an incoming request and the resources already available on network. The calculation information determines if requested-resources are more than or equal to the available reserved resources for either HC or NC. If not, the call is refused. The plan reduces HCDP and NCBP in an equitable way. Because some of the reserved resources could go unused, the plan makes wasteful use of them.

To guarantee better usage of resources, we presented an Adaptive CAC Algorithm that relies on RB allocation. Incoming call requests are categorized into RT and NRT

by the scheme, which then allocates a certain amount of resources to RT calls and uses the rest for NRT calls. It takes into account present traffic situation and changes the amount of allocated-resources for RT calls accordingly. Because resources are not delay sensitive, it puts NRT calls in a queue when there aren't enough of them. Minimizing NCBP, the technique is simple to execute. It smartly adjusts the amount of reserved resources depending on traffic, which reduces resource loss as well. However, by disregarding the handoff case, it raises HCDP.

New resource allocation method suggested to ensure quality of service for real-time and non-real-time calls. Two strategies are used by the scheme: one dynamically allocates the reserved resources to RT calls in migration and the other to NRT calls. The first strategy limits number of calls in the network and reduces the probability of block and loss by reserving resources for mobility. This strategy ensures throughput for all allowed calls, reduces HCDP, and enhances NCBP in response to an increase in number of calls with mobility.

Bandwidth Degradation (BD) Schemes

The goal of the BD schemes is to free up resources that were previously allocated to low-priority calls so that more users may connect to the network. We take look at the plans this way:

An FBPA, or Fairness-Based Preemption Algorithm, was suggested to make sure that everyone is treated equally. The FBPA carries out preemption in two stages: partial and total. Calls with low priorities and high priorities with overprovisioned resources are preempted to their appropriate GBRs during the partial preemption phase. All of the resources allocated to low-priority calls are de-emphasized at end of the preemption phase. This happens when the resources acquired during the partial preemption phase are insufficient. After the entire preemption is finished, the call is rejected if there aren't enough resources. The method is better in terms of preemption equity. In contrast, it diminishes all ongoing calls equally, regardless of the amount of resources required by the incoming call, making it a misallocation of network resources. Furthermore, a Priority-Scalled (PS) preemption method using ARP was created to ensure fair treatment of Low Priority Preemptible Active Bearers (LP-PABs). The scheme's setup makes use of both a Total Preemption Algorithm (TPA)

and a Priority-Scalled (PS) Minimum Quality of Service Preemption Algorithm (PS-MQPA). First, the PS-MQPA will preempt resources from the LP PABs whose priorities are lower on the priority list; the quantity of resources preempted increases as the priority drops. The NC calculates RTotal and RMin whenever it arrives. Reconfiguring or preempting all LP-PABs to their lowest QoS demands may liberate an amount of resources (RMin), whereas TPA can acquire a total of resources (RTotal). In the event when the NC shows up, we calculate both of these parameters. In order for the algorithm to reject the NC, RTotal must be sufficient to meet the quality-of-service requirements. Following the preemption of the PS-MQPA, the TPA will take precedence over all resources included in LPPABs if the resources remain inadequate. Due to preemption mechanism, higher priority calls may get modest service rates in quality of service (QoS), even if this approach lowers the HCDP for LP-PABs.

To maximize system capacity while guaranteeing quality of service for all service classes, a novel mechanism called Radio Admission Control (RAC) was used in. A service may be preempted if its resources are in Group 1, but services in Groups 2 and 3 cannot be preempted. These three groupings are how the system sorts services. It moves low-priority calls to their proper GBR and adds the degraded resources to the Complete Sharing (CS) pool if there aren't enough resources. In this way, any North Carolina that is in need of the resources might get them. Although the scheme improves system capacity and maintains service quality for all authorized users, it is not suitable for HCs since the handoff condition is ignored.

A method for allocating resources to RT and NRT users was introduced in as Utility Based Scheduling and Call Admission Control (UBSCAC). This method handles call admissions and is based on a persistent scheduler. The UBSCAC approach categorizes two kind of services: VoIP and video. The method use the Received Signal Strength (RSS) value to ascertain whether a channel is good or not. It dynamically reserves resources for voice over IP (VoIP), video over IP (VoIP), and calls with weak channels based on traffic density. Furthermore, the system allots resources to RT and NRT users according to largest marginal utility function. In economics, "marginal utility" is defined-as the change from the user's pre-allocation utility to their post-allocation utility after resources are dispersed to them. Finally, in

cases when resources are insufficient, the strategy prioritizes RT and NRT calls above calls made via weak channels. The strategy is good for HCDP and resource use, but it doesn't help calls with bad channel quality.

A CAC technique based on adaptive bandwidth allocation was developed to-reduce the amount of calls that are lost. Depending on traffic class they generate, the approach allots resources to NCs and HCs. In order to make room for additional calls to join their respective networks, it degrades a different amount of resources from NRT calls while an HC or NC call is requesting admission. The method not only keeps bandwidth utilization constant, but it also decreases HCDP. On other hand, NCBP increases as plan's emphasis on HCs.

A method called Utility Based Scheduling and CAC (UBSCAC) was suggested to ensure that services are-distinct from one other. Here, we classify the kind of service as either RT or NRT, and we split incoming call requests into two groups: NC and HC. To find out whether a channel is good or poor quality, the system uses the RSS value. It allocates resources to VoIP-HCs and video-HCs based on traffic density and the tolerance of limit (TOL), respectively. In order to distribute resources to NCs, the system takes the channel condition into account while computing the utility function. Channel scheduling for RT and NRT users is accomplished using the greatest marginal utility function. In event that sufficient resources are not available, the approach enables more high-capacity devices to join the network by degrading the resources of users with inadequate channels. The strategy is good for HCDP and resource use, but it doesn't help calls with bad channel quality.

In order to reduce HCDP without compromising service quality, a comprehensive DBA-CAC method was implemented. When resources are low, the system uses a load-balancing handoff technique to give more priority to HCs than NCs and queue applications. It uses DBA to predict, from the call's historical behavior, how-much resources will need to be reserved in advance. To degrade resources produced from NRT calls for NCs and HCs in queue, the DBA employs an arrival algorithm. At the end of each call, it uses a departure mechanism to free up resources for other calls that are still in progress. The strategy ensures an efficient transfer, reduces NCBP, and improves resource use. However, low-priority flows are penalized by the system, which is seen as unfair.

An approach called Fair Intelligent (LTE-FIAC) idea was introduced to ensure-that calls with different-priority classes & flows with same priority level are-handled fairly. Two ideas that the LTE-FIAC developed and put into practice are Virtual Portioning (VP) and Complete Sharing (CS).

Using a phase of variable size degradation, the approach allows higher-priority calls to be-admitted by degrading a variable amount of-resources from lower-priority calls. It not only makes blockages less likely, but it also guarantees that flows of equal or differing priority levels are handled fairly. On the other side, the system prioritizes higher-priority calls over lower-priority ones, which means that low-priority calls are more-likely to be stopped. Furthermore, it ignores handoff scenario, which raises probability of handoff being abandoned.

Providing Quality-of Service Guarantees in LTE networks-was the goal of a Fuzzy-based definitive method that was introduced in. The purpose of this method was to regulate the entry of calls. Prioritizing users-based on their categorization, quality-of service requirements, and maximum-delay tolerance for traffic takes use of network's available resources. Not only that, but it also dynamically-adjusts the user's priority based-on their categorization, assigning them to the Golden or Silver category (respectively) for RT & NRT services.

This technique also considers amount of resources required by the new connection when determining whether to completely or partially-preempt existing connections in response to a higher-priority request. Furthermore, the strategy increases the amount of resources allocated to customers as their channel quality declines. Users are assured of QoS using the process. Conversely, users with low priority would drop out at a far faster rate if they were completely preempted. Another way to decrease resource use is to increase allocation of resources with poor channel conditions. The reason for this is because resources allocated to these users run the risk of being wasted.

BR and BD Schemes

In-order to get additional calls into network, BR-BD schemes degrade previously accepted low-priority calls and reserve resources. Here are the schemes that have been reviewed:

The aim of the presentation was to find out how to decrease the chance of a handoff being obstructed by an-adjustable CAC system. system classifies-incoming call requests into three categories: No Response Time, Real-Time Tolerant and Real Time Intolerant. Moreover, it gives preference to the service classes such as NC-NRT, HC-NRT, NC-TLR, HCTLR, NC-INTLR, HC-INTLR. plan adaptively-reserves resources-for HCs in line with the service agreement. If there's not enough resources, calls whose priority is low (NRT) are degraded, and calls whose priority is higher than the basic one are degraded as well. However, if none of the methods are able to produce enough resources, HC is discarded. In addition, if there-are not enough resources, the system places NCs in one of three other queues: the NRT queue, the RT-TLR queue, and the RT-INTLR queue. To accommodate for NCs in line, the approach adjusts the NRT call quality based on the latency, if it cannot, then it stops the NC. The system operates with optimal utilization of resources while minimizing NCBP. However, queuing mechanism is unfair to NRT calls-made when resources are low and leads NCs to face lengthier delays.

Allocated a framework to dynamically adapt bandwidth for the use of a protocol Adaptive CAC method to-reduce HCDP without compromising the service quality. Once the service type of an incoming-call has been determined as-either RT or NRT, scheme also determines if call is HC or NC as per availability of resources. Moreover, it allocates-resources for HCs according to network demand, which means that if network is in low usage, it may queue the calls-when there are-no resources. In parallel, it implements dynamic Bandwidth Adaptation strategy that helps move unused bandwidth resources to other connections & reduce the bandwidth of NRT connections to enable queued NC & HC connections to be accepted. However, it is unfair to NRT-calls as it backs up HCDP & NCBP according to the latency.

An-adaptive CAC approach was developed with aim of reducing HCDP in. scheme categorizes-services as non-real-time (NRT), real-time intolerant (RTINTLR), and real-time tolerant (RTTLR). Moreover, there are-numerous types of non-real time neural networks like NC-NRT, HC-NRT, NC-TLR, HC-TLR, NC-INTLR and HC-INTLR, and these are ranked below. We achieve this by implementing a dynamic reservation system where a threshold capacity is associated with each service-class for its resource blocks. These levels are constantly-adjusted based on cell's state and the sort of blocked call's degree. In the limited resource case, the technique queues NCs to allow more calls to be processed. Also, if there are not enough resources, the

system gives lower priorities (NRT) to calls that have RBmin, and lower priorities (RBmax) to calls with bandwidth allotments higher than their RBmin. Another benefit is better use of resources which decreases-NCBP for VoIP calls & HCDP. Unfortunately, the approach is inefficient with the network's resources as it disregards channel quality.

In order to provide multimedia services, an acronym FCAC_P (Flexible CAC with Pre-emption) was proposed. Once the RT and NRT users have been identified in incoming call requests, the FCAC P will evaluate quality of the channel by using the RSS-value, and will finally make the decision as to whether call is NC or HC. The method is based on the principle of dynamically reserving resources for the real-time calls, non-real-time calls and considering the current-network load. If there are enough resources-assigned to NRT calls, it will accept a NRT protocol call irrespective of channel quality. If you do not comply, the call will be rejected. In the case-of limited resources, it discards HCs with-bad channels and labels RT-calls with good channels-as RT HC or RT NC, regardless of the channel. In this way, RT HCs are granted automatically while RT NCs-are granted with certain probability. There are two types of NRT calls in system, both long running and not pre-empted, which are pre-empted to-free up the resources for RT. Non-pre-empted NRT-calls have a threshold set. The approach will lower the NCBP for high priority-calls and improve throughput. However, it will have an undesirable side effect on low priority calls, due to the NCBP rise caused by its pre-emption mechanism. The idea of a multiservice CAC-(MSCAC) was proposed in with aim of bolstering multimedia services. Conversational (including real-time services like VoIP), streaming (including real-time services like video), and best effort (including non-real-time services like FTP) are the three types of multimedia services that are given a queue by the MSCAC technique. This approach is broken down into two parts: VoIP-HCs and BE & public resources. The former group are resources consumed by BE, video and new VoIP calls, and the latter group are allocated according to rate of VoIP traffic. If it has a full queue it won't accept any further calls and it will remove calls from the queue after they have expired due to delay time-out. If there are not enough-resources for VoIP high-capacity clients to use, the MSCAC will call them via public allotted resources. The method ensures that there is minimum chance of blocking on all class types and also-minimises wasted resources. In the meantime, it is not fair to NCs: it takes away resources that should be-allocated to NCs & it takes away resources that

should be-allocated to NCs to service-VoIP HCs.

In non-real-time traffic, an Efficient-Channel State Based CAC (CBECAC) was proposed to-ensure the optimum utilization of resources. CBECAC system consists of three steps: call categorization, channel-state estimation and call admission control. On incoming call request, they are-classified into two classes: NC and HC in the call classification phase. The HC requests are given precedence over the NC ones. Then each class is further categorized as either RT (VoIP) or BE (video) – where RT is used for prioritizing VoIP and BE is used for video. The RSS value is used in the channel estimate implementation to determine if a channel is great or bad. amount of resources reserved for the VoIP, video & low-quality channel calls steps in call admission-control phase is dynamic based on volume of traffic. It decreases quality of resources used in bad channels in order-to have other calls accepted if there-are not enough resources. Although this has an advantage in terms-of resource utilization, it is unfair to NCs because of strong emphasis on HCs in the strategy.

An Adaptive CAC-Scheme based on higher-order Markov chain was also introduced to deal with NCBP in an appropriate way. The PRB allocation technique is used to construct the allocation intelligently and the system uses the model of resource allocation Markov chain. Moreover, it allocates-resources to HCs based on traffic volume, making optimal use of resources available to manage all HC calls. In addition, it helps decrease number of calls that are not as important so it can accommodate more calls-when resources are scarce. The NCBP system, which is adaptable to all types of traffic, keeps track of resource use. But it's not fair to-degrade the calls with-low priority, because of degrading process in use.

It was-proposed to use an Adaptive-Call Admission Control with-Bandwidth Reservation for the best utilization of resources and to avoid the BE connections from getting hungry. The approach dynamically allocates resources-for handoff connections based on handoff traffic. Moreover, it is able to handle both real-time (RT) connections and non- real-time (NRT) connections, each with different minimum and maximum resource requirements.

It applies a BD technique on the reduction of quality of the RT calls when-resource is limited. On other hand, if the degraded-resources are not able to meet the increased demand, the link will be severed.

Rates of blocking and dropping are both reduced by the system. It is true that the BD procedure reduces RT connection throughput; this is because it degrades resources before determining whether they are sufficient.

As a result, reducing the transmission-rate of existing RT-connections does not prevent calls from being discarded when degraded resources-are insufficient to receive the requested call. This continues to occur even after the call that requested it is ended.

Non-BR and Non-BD Schemes

Resources are neither assigned to current calls nor those reserved for future usage are degraded by the NR-ND methods. Here are the reviewed schemes:

To ensure-service quality, developed RECAC (Resource-estimated call admission control). The RECAC-scheme can predict number of PRBs required for an incoming call, depending on type of service and Modulation & Coding Scheme (MCS). If the number of resources available is greater-than minimum number of resources then scheme will accept incoming call. Not-only does this method lessen NCBP, it also lowers average-packet delay. On other side, it saves resources as it only requests calls that have the lowest data rate request. Another reason for the system to raise HCDP is that when the HC requests to be coded, they are coded at a lower coding rate than the NC.

Numerous CAC methods were proposed based on Bayesian and neural network principles to improve performance of the network. BN method considers incoming call when probability of all-ongoing GBR calls to have a higher QoS than a threshold minimum-system QoS threshold value, and uses estimation of probability-distribution of the QoS of-ongoing calls. If an incoming-call is below a certain threshold, NN scheme will allow it; otherwise, it will evaluate all active GBR calls' QoS and reject incoming call. Each of these systems adjusts allocation-of resources dynamically in response to the state of channel and mobility of the user. Although the NN CAC-scheme outperforms the BN CAC scheme in terms of prediction accuracy, the BN CAC system actually has lower error rate. These strategies not-only provide high-quality service, they are also efficient use of resources that are available. However, if rejection of the calls based on QoS-threshold and probability of BN-scheme is inappropriate, it may result in wasted resources.

To enhance the service quality in, we have proposed fuzzy-based call-admission control system. In fuzzy method, calls are received based on number of available-channels and the current state of network. Additional capabilities of the technique are channel aggregation, resource-allocation to the needs of either-NC or HCs & the estimation of the condition of call channels. It determines the call channel state as well. However, if there aren't enough resources, the call will be sent to a queue and attempted again after four attempts before being rejected or blocked. Both customer satisfaction and service quality are enhanced as consequence of the strategy. But it does-not cope well with very low and very high channel conditions, respectively, which results in sub-optimal resource-management for the network.

A Hybrid-Adaptive Call Admission Control-Mechanism was created to reduce amount of HCDP. The system uses a resource block technique to allocate resources depending on type of call (NC or HC). When deciding which calls to prioritize, it takes into account the following parameters: the maximum and least acceptable latency and delay, as well as amount of RBs needed. To prevent calls that go beyond their delay time-out, the system additionally has an expiration delay. This occurs when call volume is greater than apacity of the resources. The strategy allows for better use of resources and lower HCDP. The system does not concern with channel state beyond the admission time, so, it raises NCBP & cannot ensure service quality if channel state is not static.

To guarantee different types of traffic quality of service, a suggested algorithm called Delay-aware Call-Admission Control (DA-CAC) was designed. Currently, the DA-CAC (DD-CAC) algorithm uses statistical information regarding packets' latency and the usage of PRB. The strategy also uses a dynamic moving window average to compute the mean connection holding time. This approach has many smaller windows, between each time call is requested size of each window is determined by the time that passes.

In order to keep the network from being overloaded, the technique is programmed to reject some calls. It lessens HCDP overall, which lowers packet latency for all-service classes. Nevertheless, the system's strategy of-rejecting certain call-requests to reduce congestion causes a decrease in resource-utilization and average data rate overall. This also leads to an increase in NCBP.

To avoid congestion & ensure quality of service, a strategy for allocating resources and controlling call admissions based on service quality was proposed. Using a speech monitor, the plan may record current talks, assess call quality in real-time, and spot problems as they happen. It replaces speech probing streams with metrics collected from actual VoIP conversations, which allow for dynamic resource distribution depending on changes in call quality. In addition to producing high-quality voice calls, the method improves-resource utilization. Having said that, it isn't great for multi-service networks as it just considers voice calls.

A technique that can-be used for effective control of resource usage is the DA-UC-ARR technique (delay aware user classification & adaptive resource reservation-based call admission control). Construction of DA-UC-ARR system requires two sub-schemes that are used for-construction of the system. Among these sub-schemes, there are two, one of them is based on-user categorization (UC-ARR) and the other is based-on user categorization and adaptive-resource reservation (DA-UC-ARR). UC-ARR is a system for categorizing the user requests into two main categories, Golden (G) and Silver (S). It also divides the services each gives to the users into two more general categories: RT & NRT. Adaptive virtual resource reservations are also-made for G RT, S RT, G NRT and S NRT under the method. If it has the resources, it will accept a call request, otherwise it will place it in its queue and process the request having the lowest Adaptive Priority (AP). The two factors taken into consideration when determining administrative power (AP) are: total-number of resources currently-consumed by all users of that service class & user type; and number of virtual reserved-RBs for calls of that class & user type.

1.6 STATEMENT OF AIM

This project's goal is to enhance mobile network performance by introducing an AI-driven Call Admission Control (CAC) system. Traditional CAC approaches often have difficulty effectively managing the growing demand and complexity of mobile networks, which results in inefficient resource usage and a decline in quality of user experiences. Through use of artificial intelligence, we are able to create a CAC mechanism that is dynamic, data-driven, and capable of intelligently predicting network circumstances, optimizing resource allocation, and prioritizing call handling. This forward-thinking strategy aims to eliminate call dropouts, reduce latency, and enhance overall service quality. As a result, it provides customers with a mobile communication experience that is more resilient and dependable.

Therefore, the title of our study is, *"IMPROVING MOBILE NETWORK PERFORMANCE WITH AI-POWERED CALL ADMISSION CONTROL (CAC)".*

1.7 NEED AND SCOPE OF THE STUDY

Need of the study

The ever-increasing demand for high-quality mobile communication services, as-well as the constraints of Call Admission-Control (CAC) procedures that are already in place, have resulted in the need of conducting this research. The old CAC techniques are not-enough for effectively managing network resources in light of fact that mobile networks are becoming-more crowded as result of the growth of smart devices and apps that need a significant amount of data.

Because of this, phone calls are dropped often, the latency is excessive, and the user experience is subpar. For effectively handle these difficulties, it is vital to implement a CAC system that is driven by AI. Artificial intelligence has the potential to greatly improve network performance by intelligently forecasting network circumstances and optimizing resource allocation.

Scope of the study

The goal of this project is to enhance mobile network performance by the implementation of an AI-driven Call Admission Control (CAC) system. entails its development, deployment, and assessment. It involves development of

sophisticated machine learning-algorithms that are able to forecast the state of the network and optimize the distribution of resources in real time. The project gathers and analyzes a substantial amount of data from mobile networks in-order to train and evaluate these artificial intelligence models, ensuring that they-are accurate and effective. In-addition, project investigates the possibility of incorporating the AI-powered CAC system into pre-existing network infrastructures.

This is followed by extensive testing to evaluate its performance in comparison to conventional CAC approaches. Key performance indicators such as call drop rates, latency, and resource consumption, in addition to user experience metrics, are measured to determine the impact on the effectiveness of the service.

The research investigates the scalability and flexibility of the system to guarantee that it is capable of managing wide range of network circumstances and user demands. This allows for a comprehensive understanding of the potential advantages and disadvantages of the system.

1.8 OBJECTIVES OF THE STUDY

Following are the main objectives of this study: -

1. To develop and implement AI-driven CAC schemes to enhance QoS and resource utilization in mobile multimedia networks.
2. To implement mobility-driven CAC for resource estimation in wireless networks.
3. To optimize resource allocation with ANN-based channel allocation in mobile multimedia networks.
4. To implement neural-fuzzy CAC for QoS assurance.

1.9 HYPOTHESIS OF THE STUDY

The hypothesis for the study on Admission Control (CAC) schemes leveraging-artificial intelligence-techniques for optimizing mobile multimedia networks posits that integrating AI-driven CAC algorithms into mobile networks enhances network performance by efficiently managing resource allocation, reducing congestion, and

prioritizing multimedia traffic, ultimately leading to improved quality of service and user satisfaction.

1.10 DEFINITION OF THE KEYWORDS

Mobile Network Performance: The effectiveness and efficiency with which a mobile communication system provides services to its users, typically measured by various parameters like data throughput, latency, connectivity, and call quality.

AI-Powered: Utilizing artificial intelligence (AI) technologies, such as machine learning algorithms, to enhance or optimize processes. In this context, it means use of AI to improve the decision-making processes within the network.

Call Admission Control (CAC): A network management function that determines whether to accept a new incoming call or session based on current network conditions and resource availability. Its primary goal is to maintain the desired quality of service (QoS) for ongoing calls and data sessions.

Artificial Intelligence (AI): The simulation of human intelligence in machines that are programmed to think and learn like humans. AI applications in telecommunications can include predictive analytics, automated network management, and optimization tasks.

Quality of Service (QoS): A measure of the overall performance of service or network, particularly in terms of its ability-to provide users with reliable and satisfactory service levels. In mobile networks, QoS parameters include factors like bandwidth, latency, jitter, and error rates.

Network Optimization: The process-of enhancing performance of a network by adjusting its configuration and resource allocation to achieve optimal efficiency and service quality. AI can play significant role in automating and improving these optimization processes.

Resource Availability: Availability of network resources, such as bandwidth and processing power, to handle new calls or data sessions. Efficient management of resource availability is crucial for maintaining QoS.

1.11 LIMITATION OF THE STUDY

Generalization: The study may be limited in its ability to generalize findings beyond the specific context in which the research was conducted. Factors such as network infrastructure, user behavior, and geographical location can vary widely, potentially limiting the applicability of the findings to other settings.

Data Availability and Quality: The effectiveness of AI algorithms heavily depends on the availability and quality of data. Limitations in data availability, inaccuracies, or biases in data used for training the AI models could affect reliability and generalizability of study results.

Model Complexity and Interpretability: AI-powered call admission control systems may utilize complex machine learning models whose workings are not-easily interpretable. This interpretability makes it challenging to understand-why certain decisions are made to validate and refine the model.

Performance Metrics: Choosing appropriate performance metrics to evaluate effectiveness of AI-powered call admission control is crucial but challenging. Metrics such as call drop rates, call setup time, and network utilization may not fully capture the user experience or the impact on overall network performance.

Dynamic Network Environment: Mobile networks are inherently dynamic, with varying traffic loads, user mobility, and environmental conditions. This study-may not account for the full spectrum of dynamic factors that influence network performance, potentially limiting the efficacy of the proposed AI-powered solution in real-world scenarios.

Resource Constraints: Implementing AI-powered call admission control systems may require significant computational resources and infrastructure. The study may not fully consider the practical challenges and resource-constraints associated with deploying and maintaining such systems, especially in resource-constrained environments.

Ethical and Privacy Concerns: AI algorithms may inadvertently perpetuate or exacerbate biases present in the data, leading to unfair or discriminatory outcomes. Additionally, the collection and analysis of user data for AI training purposes raise ethical and privacy concerns that need to be carefully addressed in the study.

Human Factors: study may not adequately consider impact of human factors such-as user preferences, behavior, and expectations on the effectiveness of AI-powered call admission control. Ignoring these factors could lead to discrepancies between the expected and observed outcomes of system.

External Dependencies: performance of AI-powered call admission control systems may be influenced by external factors such as regulatory policies, market dynamics, and technological advancements. Failure to account for these external dependencies could limit the robustness and scalability of the proposed solution.

Long-term Sustainability: The study may focus on short-term improvements in mobile network performance without considering the long-term sustainability and scalability of the AI-powered solution. Factors such as evolving network technologies, user demands, and economic considerations need to be considered for sustainable deployment and operation.

1.12 DELIMITATIONS OF THE STUDY

This study-focuses on application of AI-powered call admission control (CAC) specifically within mobile network environments, intentionally excluding fixed-line networks and other telecommunication services. The primary aim is to analyze the performance metrics of mobile networks, such as call drop rates, latency, and user satisfaction, in the context of CAC, which narrows the scope to voice services and does not encompass data services or multimedia communications. Furthermore, the research is limited to specific mobile network technologies, including 4G and 5G systems, without considering legacy systems like 2G and 3G. This decision is based on the increasing reliance on newer technologies and their unique challenges and opportunities. The study also restricts its geographical focus to urban areas, where mobile network congestion is more prevalent, thereby excluding rural or less-densely populated regions that exhibit different network behavior. Additionally, the investigation will utilize simulated network environments rather than real-world deployments. This approach allows for controlled experimentation but may limit the generalizability of findings to actual operational scenarios. Lastly, the study will emphasize quantitative data analysis, sidelining qualitative insights that could provide

more comprehensive understanding of user experiences and perceptions regarding mobile network performance.

1.13 RESEARCH METHODOLOGY

PHASE I– MOBILITY-BASED CAC AND RESOURCE ESTIMATION MODEL USING ANN

In this section a mobility-based Call Admission Control (CAC) and resource estimation using Error Backpropagation Neural Network (EBP-NN) and Queuing model have been proposed. In this EBP-NN have been used to find the exact and accurate future handoff location of Mobile User (MU) to select the right Base Station (BS). Further, the queuing model have been implemented to reserve enough number of resources to handle handoff calls. It reduced the Call Dropping Probability (CDP) and increased resource utilization.

PHASE II- DYNAMIC CHANNEL ALLOCATION USING– HOPFIELD NEURAL NETWORKS FOR CONFLICT-FREE CHANNEL MANAGEMENT

Channel allocation problems of mobile multimedia networks using Hopfield Neural Network (HNN) have been discussed. In this-section, an HNN based fitness function have been formulated to handle channel allocation problems. The model has been implemented on four benchmark channel allocation problems i.e. HEX 1, HEX 3, [SMIT97], [BATT01], KUNZ 1 and KUNZ 2 [KUNZ91].

PHASE III- NEURAL FUZZY-BASED CALL ADMISSION CONTROL FOR ENHANCED QOS IN HIGH-SPEED MOBILE MULTIMEDIA NETWORKS

In this phase a new QoS provisioning based CAC approach which use a combined approach of NN and FL. Basically this model is implemented in two phases the first phase used the self-organized learning scheme for the construction of fuzzy rules and membership functions, and in second phase used supervised learning scheme for the ideal adjustment of the membership functions to achieve desired outputs in terms of acceptance and rejection of calls, to maintain the QoS requirements at different traffic load.

1.14 PLAN OF WORK

Chapter 1: Introduction

This chapter provides comprehensive overview of the project, outlining the problem statement, objectives, and significance of improving mobile network performance using AI-powered call admission control (CAC). It introduces key concepts and terminologies, emphasizing importance of efficient resource-management in mobile networks, especially with the increasing demand for high-quality multimedia services.

Chapter 2: Review of Literature

The literature review covers existing research on call admission control, focusing on traditional methods and recent advancements involving AI techniques. It explores various approaches to CAC, including rule-based systems, optimization algorithms, and AI-based models, such as-machine learning and neural networks. The review highlights gaps in current research, particularly the need for more adaptive and intelligent systems to handle dynamic network conditions and diverse Quality of Service (QoS) requirements.

Chapter 3: Mobility-Based Cac and Resource Estimation Model Using Ann

This chapter discusses the integration of mobility models into call admission control to improve resource estimation and management. It examines how user mobility patterns impact network performance and resource allocation. The use of AI techniques to predict user movements and optimize resource distribution is explored, along with case studies or simulations demonstrating the effectiveness of these methods.

Chapter 4: dynamic channel allocation using Hopfield-neural networks for conflict-free channel management

Here, the focus shifts to channel allocation strategies in mobile multimedia networks, utilizing artificial neural networks (ANNs) for decision-making. The chapter explains how ANNs learn from historical data to allocate channels dynamically, ensuring optimal utilization of available bandwidth and maintaining QoS. The benefits of using ANNs, such as adaptability and real-time processing, are highlighted, along with comparative analysis against traditional allocation methods.

Chapter 5: neural fuzzy-based call admission control for enhanced qos in high-speed mobile multimedia networks

This chapter explores the application of neural-fuzzy systems in call admission control, combining the learning capabilities of neural networks with the interpretability of fuzzy logic. The hybrid approach enhances decision-making for QoS provisioning, especially in complex and uncertain network environments. The chapter details design and implementation of neural-fuzzy CAC model, supported by experimental results demonstrating its efficacy in maintaining QoS standards.

Chapter 6: Conclusion

This chapter summarizes the major findings and contributions of the study. It reflects on the effectiveness of AI-based approaches in improving network performance.

Chapter 7: Recommendation

This chapter provides practical suggestions for implementing AI-based CAC models. It focuses on improving real-world mobile network efficiency.

Chapter 8: Future Scope

This chapter outlines potential future research directions. It highlights the scope for advanced AI techniques in next-generation mobile networks.

CHAPTER 2
REVIEW OF LITERATURE

[1] Increased handoffs between calls are a result of customers becoming more mobile and mobile networks having less accessible wireless resources. The quality of service (QoS) in wireless networks is harmed by these problems because of inadequate resource reserve and careless admission control. Reducing the high call drop rate, delay response time, and traffic congestion requires an efficient call admission technique. The investigation led to the suggestion of a call admission strategy based on fuzzy logic. Intelligent call management and call handoff are now standard features of Long-Term Evolution (LTE) networks. The proposed efficient call admission control system utilized fuzzy logic controller-for intelligent queue management at the base station. The suggested system used drop call probability, average queue length, and queue size to evaluate fuzzy & non-fuzzy alternatives. The results show-that network performance has significantly improved, with fewer call dropouts occurring.

[2] A comparison and contrast of three distinct mobile network operators (MNOs) was the focus of this research project, which investigated the mobile network service in Ibogun, which is located in Ogun State, Nigeria. In-order to carry out the performance evaluation, driving tests were-carried out with the assistance of transmission environment monitoring software (TEMs), and statistical analysis was undertaken simultaneously. The results-indicate that the poor quality of the mobile networks is attributable to the receive signal strength level, which was discovered to be between -50 dBm and -110 dBm. This is in contrast to the -30 dBm to -70 dBm that was advised by the Nigerian Communication Commission (NCC). In terms of the upload and download speeds for data services such as short message service (SMS), it was

discovered that the network services provided by the different providers differed in terms of performance. GLO was determined to have the poorest performance, while MTN had the highest performance.

[3] There is no need for synchronization with surrounding cells when using the Soft-Handover or connected-before-break approach, which ensures that the user equipment (UE) remains connected to the radio connection at all times. As a consequence of this, the user equipment (UE) creates a delicate connection with several NodeBs at the same time. There are alternatives to long-term evolution (LTE) networking that depend on orthogonal frequency division multiplexing (OFDM). One of reason for this is incompatibility of 4G networks with soft-handover. 5G networks, on other hand, may provide a smooth soft-handoff from one cell to another nearby. An intelligent call admission control (CACA) algorithm is a must-have for 5G networks in order to guarantee end customers a suitable quality of service (QoS). The reconnection procedure will go off without a hitch because of this. The research culminates in a novel multi-cell CACA solution that can-be implemented in 5G networks. Given that process known as "cell breathing" causes the overloaded cell coverage to decrease, the CACA that is evaluated is the one that is taken into consideration. The user's admission is determined by a minimum bit rate, the maximum distance from the base station, and the maximum number of active users in the cell. The numerical findings demonstrate that the proposed CACA is successful in decreasing network congestion. This is accomplished by moving traffic from cells that are overloaded to cells that are nearby and have a lower load. Furthermore, this impact is exhibited across a wide range of interference factor values, which ultimately leads in enhanced network performance. In order to demonstrate that the CACA is effective, we analyse results that were obtained both-with and without the implementation of the suggested CACA.

[4] the development of new generations of mobile networks has occurred concurrently with the proliferation of mobile telecommunications networks. These network systems have made it possible for new services to be included into their operations. Because-of the rapid advancement of technology, the complexity of network has expanded as result of the operators' adaptation of planning strategies to accommodate implementation of new technologies. A number of factors, including ideal radio coverage, handover management, interference prediction, cell size, supported load, and

compatibility with existing networks, are all taken into consideration throughout the design process. In the event that-there is an increase in amount of traffic, this will guarantee that consumers will continue to get coverage and service that meets their expectations. The fundamental objective of this endeavor is to supervise the methods for sizing, designing, and optimizing 4G networks. During the course of this inquiry, the numerous factors, including PDSCH Modulation and BLER, which stands for Block Error Rate, were examined and found to be relevant.

[5] Researchers in Malaysia investigated the performance of Mobile Broadband (MBB) services over urban terrain by using experimental assessments of driving test data. These services were supplied by mobile networks of the Fourth Generation (4G) and the Third Generation (3G). The primary objective of the research is to give assistance to service providers in formulating a workable plan for development of future 5G networks. In order to establish groundwork for our present endeavor, we used findings from our past-research on size of Malaysia's rural areas. In-order to evaluate and study the performances of MBB, the measurement data was obtained from driving tests that were-carried out in the metropolitan areas of four states in Malaysia: Klang Valley/Selangor, Johor, Sarawak, and Sabah. These states are located in Malaysia. All three of the most prominent Mobile Network Operators (MNOs) were involved in the process of collecting data, which included information from the metropolitan areas, highways, and federal roads of the states that were chosen. Over the period of two months, beginning in January and continuing through February, information was obtained via the use of Samsung Galaxy S6 mobile phones. Mobile broadband (MBB) service coverage, latency, customer happiness, and speed are the four KPIs considered in this research. Two MBB-services that are currently being thought about include streaming videos and surfing the web. A specific smartphone was used to gather the measurement data that defines the performance of each MBB service. Using YouTube videos streamed sequentially at 720p and 1080p resolutions, this experiment aimed to assess performance of MBB video-streaming services. In order-to evaluate the functionality of the web browser that comes with MBB, we used three distinct websites: Google, Instagram, and mStar. The experimental technique used in this work involves a variety of different components in order-to replicate the situations that are seen in the actual world. Four distinct metropolitan states, four distinct key performance indicators (KPIs), three primary mobile network operators, two mobile broadband services, and

two radio networks (fourth generation and third generation) that can-be accessed by smartphones when-they are accessible are all included in this category. Generally speaking, the outcomes of the research indicate that 4G radio networks function better than 3G ones. For instance, in each of the four areas of inquiry, 4G networks achieved a vMOS score that-was more than 3, but 3G networks achieved score that was lower than 3 for internet browsing and MBB video streaming services. When-compared to 3G networks, 4G networks provide a download speed gain of up to 1.6 times for video streaming and 4.2 times for web browsing. This is-according to results of the experiment that was reviewed. results of research might be of assistance in the efficient development of NSA networks in Malaysia, as 5G networks would make use of the infrastructures that are already in place for 4G networks. To ascertain the rate at which the National Security Agency (NSA) would roll out 5G in Malaysia, it is-required to do an analysis of performance of 4G coverage.

[6] There is an increase in number of people using wireless cellular networks; nevertheless, the capacity of wireless communications is limited. Due to fact that this network receives a significant amount of traffic and its users have frequent requests, it is vital to make the most efficient use of the resources available on the network. Additionally, during congestion periods, resource swings and changes in channel quality may occur because of user movement. For maintaining quality of service (QoS), cells need extra resources. It is required-to implement a Call Admission Control (CAC) approach in-order to limit mobile users depending on the resources that are available instantly. A fundamental problem in wireless networks is to maximize resource utilization by permitting a greater number of calls while maintaining the quality of service of the services that are already in place. This method provides a solution to the problem. We emphasize the relevance of CAC in this present communication time and classify it based on the literature; especially, we give a comprehensive idea of CAC strategies in wireless cellular networks. After presenting and researching variety of approaches to implementing CAC, as well as variety of design characteristics of CAC schemes, we conclude by highlighting number of research obstacles and challenges that will be faced by future generation wireless networks.

[7] People have a strong belief that mobile networks (MN) would make previously inconceivable possibilities for a flood of new experiences that are connected to one another available to them, so totally transforming the manner in which people interact with the world around them. MN are getting increasingly difficult to manage as a consequence of the constant emergence of new service requirements and the development of more complex configuration difficulties. The deployment, administration, operation, optimization, and maintenance processes are all made much more challenging by this complexity. This is because of fact that they need a thorough understanding and awareness of cloud computing. Artificial intelligence (AI), which is concerned with the modeling of intelligent behavior in computers, could be able to grasp the situation of MN and make intelligent judgments, given its enormous success in many application industries. This is a possibility since AI is concerned with modeling intelligent behavior in computers. Our investigation starts with a proposition for an artificial intelligence-driven mobile network architecture, which is then followed by a description of the challenges that our study has faced. These challenges include high-dimensional action space decision-making, cognitive complexity, and self-adaptation to system dynamics. Following that, we will be discussing some-potential solutions that are associated with AI. Last but not least, for combine thinking with decision- making, we provide a deep learning approach that establishes a direct connection-between the condition of the MN and quality of service that is perceived. Our recommended strategy assists operators in making better decisions, which helps to assure quality of service. At the same time, our proposed strategy is to show the effective and favorable on a real-world dataset consisting of $31261 users over $77 stations in only five days.

[8] the mobile telephone is recognized as one of technologies that is most-widely used in the modern world. The records of the usage behavior of mobile users might potentially give Mobile Network Operators (MNOs) with substantial information that can be-used for understanding the behavior of networks. Mobile network operators (MNOs) are-interested in the performance of various cellular network technologies (CNTs) in relation to region, phone category, and operating system (OS) in-order to have better understanding of their competitors. As result, mobile network operators (MNOs) could be-able to make more educated investments in regions where their performance is deficient. As a result, it is important for all mobile network operators

(MNOs) to compare their Key Performance Indicators (KPIs). In this research, statistical comparisons of cellular network performance across Turkey's main Mobile Network Operators (MNOs) are investigated. Dataset-used for this study is a vast, private, real-world mobile traffic dataset that was gathered over the course of 18 months. We are able to accomplish the following by focusing on particular aspects of the crowdsourced dataset: (i) we are able to compare the end-to-end network performance of mobile network operators (MNOs) across the country by using real-world measurement data; (ii) we are able to determine the Confidence Intervals (CIs) for the mean difference of key performance indicators (KPIs) such as downlink speed, latency, jitter, and packet loss; and (iii) we discover that MNOs differ significantly in performance based on operating region, phone category, operating system, and C networks.

[9] in this study, we use AI techniques to look into the cell association problem that tiny base stations (SBSs) have in densely crowded wireless networks. Users compete to maximize their data rate by making the most of their own data and their neighbors' data in a mean-field game setting. Since users don't have to send and receive data via the cellular network's sluggish backhaul lines, this approach of shared learning allows them to collectively update their cell association policy with minimal computational needs. We propose a neural Q-learning learning approach that makes use of a neural network to predict a user's reward function using local data and the SBSs selected by their neighbors; this allows us to overcome the aforementioned problem. Simulation results show that the imitation-based procedure proposed for cell attachment rapidly converges to the optimal solution, surpassing more conventional methods.

[10] Mobile network operators (MNOs) are now primarily concerned with the delivery of internet services that are of a high-performance level with high bandwidth. The construction of the fourth-generation mobile network, also known as 4G/LTE, was done in response to the demand from customers for faster data transfer services. The monitoring and optimization of mobile network performance via use of Key Performance Indicators (KPI) is a crucial component in-order to optimize resource usage and maintain a high level of service quality. These parameters-are divided into the following subgroups according to criteria established by the Third Generation Partnership Project (3GPP): availability, accessibility, mobility, integrity,

and retain ability. The monitoring of some of these indicators may be done on a network level, while the monitoring of others can be done on a cluster level. Within the scope of this investigation, the mobile service provider Telecom of Kosovo (TK) was used as a case study. A 4G/LTE network cluster consisting of 24 cells that has been installed in TK is the focal point of focus for the measurements and analysis that are about to take place. This investigation is being conducted with the intention of determining whether or not the 4G/LTE network is capable of meeting the performance standards that have been established by the 3GPP standard and the manufacturers.

[11] the use of artificial intelligence allows the resolution of difficult problems in the fields-of science, technology, and practical application. Artificial intelligence (AI) techniques that are widely-used for optimization, prediction, and management of communication systems include neural-networks, fuzzy systems, genetic algorithms, and evolutionary algorithms. These are some of most common AI approaches. Artificial intelligence has-potential to enhance cellular network operations such as call-admission control, handover, routing, & traffic prediction. These are-all complicated processes that take place in cellular networks. The heterogeneous networks that are meant to manage huge numbers of users while-maintaining a high level-of service quality are expected to be used with 5G mobile communications. Controlling the admittance of calls is an essential component in achieving the desired level of service. In-order to achieve optimal performance of cellular network, it is necessary-to implement a call admission-control system that is not only efficient but also effective. There are great number of call admission control mechanisms that have been offered. In this paper, a strategy is presented for the development of a genetic neurofuzzy controller that-may be used by 5G networks in-order to accept calls. For the purpose of evaluating the effectiveness of proposed admission control, a computer simulation is used.

[12] as a result of prevalent use of smartphones, there has been parabolic growth in both the type of mobile network performance evaluation indicators and amount of mobile-data that has been acquired. The identification of method that is both accurate and timely for evaluating performance of mobile networks has become challenge for mobile network-operators as result of this. This study provide method for assessing efficiency of mobile networks. The method is based

on multivariate-time series clustering with auto-encoder. The first thing that has to be done in-order to implement this-strategy is to make use-of a mix of Pearson's correlation coefficient and lightgbm in-order to eliminate some of indications that are very repetitious. Furthermore, in-order to estimate the distance matrices of multivariate time series that include the alterations in indicators throughout the course of time, we make use of fast DTW and auto-encoder algorithm. At the end, we-make use of k- medoids on matrices in-order to divide the indicator data from different time periods into three distinct portions. We discover that the clusters indicate varying degrees of mobile network performance as assessed by the provider's key performance indicators when we apply this methodology to given data that was provided by mobile network operator.

[13] The difficulties of wireless network performance prediction and the ways in which machine learning technologies could be of assistance are the primary focus of this study. When direct-measurements are not available, these difficulties often include making do with the data that is currently available for measurements in-order to anticipate performance of network. In this-paper, we provide a fundamental taxonomy of significant-problem categories & analyze the degree to which existing-machine learning algorithms are able to effectively address these challenges. use of a large-scale dataset consisting of real-world driving tests allows us to show that standard-machine learning approaches like as random forests, exponential smoothing of time series, and Gaussian process regression are capable of producing predictions that are very accurate. By applying these concepts to the management of wireless mobile networks, it is feasible to enhance the user experience while simultaneously reducing operational expenditures by a significant amount. In-addition, we discuss some of most significant challenges that will need-to be conquered in order for this work to proceed, especially with regard to the actual implementation of machine learning-algorithms for the purpose of forecasting performance in mobile wireless networks.

[14] With the advent of 5G cellular networks, millions of gadgets will be able to communicate with the network via a multitude of apps. Wearables, smartphones, tablets, and the IoT (Internet of Things) are all components of this network. To avoid network overload, 5G cellular networks must be capable of handling the massive

amounts of data produced by these devices. It is for this-reason that C-RAN has been heralded as a game-changing innovation for 5G, since it enables requests from mobile devices to be processed in the cloud via use of shared baseband processing. CAC, which stands for call-admission control, is a system for managing-radio resources that has been largely-overlooked in recent times, despite fact that it has the potential to decrease congestion on networks. When it comes to 5G C-RAN, the CAC strategy has an impact not only on the overall efficiency of the system but also on the quality of service (QoS) for individual connections. The purpose of this study is to offer a novel CAC strategy that is based on fuzzy logic and integrates preemption in C-RAN. It is suggested in this proposal that during times of congestion, the cloud bursting strategy should be used to preempt and outsource to a public cloud those low-priority connections that are tolerant of delays, although at a penalty price. According to the results of the simulation, the approach that was recommended has a low blockage probability (more than 5%), a high throughput, a low energy consumption, and a return on revenue (ROR) of up to 95%.

[15] According to the standards that were established by the Third Generation Partnership Project (3GPP), the Long-Term Evolution (LTE) network standard outlines the requirements that must be met in-order to offer Quality of Service (QoS) for variety of activities. These applications include voice-over internet protocol (VoIP), video streaming, & web browsing. When it comes to providing these guarantees, Call Admission Control Schemes and other Radio Resource Management (RRM) techniques are very necessary. It has-been recommended that variety of solutions should-be used in order to manage resources while simultaneously providing wireless apps with quality of service. This research takes a look at various call admission control (CAC) policies and procedures. The classification of algorithms such as this one is determined by whether they prioritize resource degradation or delay awareness. These algorithms may be classified as CAC with Pre-emption, RR, RD, DA, or CA. This contains an examination of the running procedure of each scheme, as well as discussion of the benefits and drawbacks associated with each plan. In-addition to this, we provide a comparison analysis of number of other designs. The analysis provides insights regarding research topics that have-not yet been solved, which might be used for future studies.

[16] When it comes to deciding whether or not the system will be successful, one of most important factors to consider is the Quality-of Service (QoS) that certain customers become acclimated to. The assessment of performance of cellular mobile networks is the primary emphasis of this present research. Approach to the Research: The mobile communication cell in issue is the network that is being referred to, and it is expected that the number of customers (m) who are making the calls is restricted. When two channels have been marked as guard channels, it is not-possible to receive any new calls on those channels. Furthermore, in order to address the problem of unwanted phone calls, a 'b' element has been included and carefully examined. When we were trying to solve the steady-state equations of the model, we used the matrix recursive technique. It is-not true, as we discovered, that behavior of consumers will not have an effect that cannot be ignored on performance of the network. This is particularly true as number of customers rises and network gets more intricate. The purpose of-this research-is to investigate the ways in which various parameters influence quality of service provided by a mobile cellular network. Additionally, it was found that in the event that a spam call is received, it will not be brought to the attention of the server and will be blacklisted. Specifically, this conclusion refers to spam calls and is a novel discovery for this research. MATLAB and the matrix approach are used in-order to solve the equations that are associated-with the steady-state. On basis of numerous state probabilities that have been obtained and the various performance measures that have been analytically formulated, numerical simulation is carried out. With regard to KPIs such as success rate of new calls & handover calls, for instance, we investigate how the retry rate influences these data. The information that illustrates the sensitivity analysis of many factors on performance indicators is presented in number of different graphs and tables. Uses that might be possible: All things considered; this study is an inquiry that is predicated on applications. A possible interpretation of this is that it is method for applying the notion of retry queueing to communication and mobile networks. Furthermore, mobile and communications systems could be-able to profit from its first installation.

[17] since number of mobile phone users continues to soar, it is imperative that service providers maintain a high standard of quality of service (QoS). Call blocking and call dropping are two indicators that are frequently used to rate a provider's quality of service. High altitude platforms (HAPs) are now being researched as a viable

solution for providing mobile communication services due to the many advantages they provide. In this paper, we present a more efficient CAC approach to answering phone calls. Our novel CAC approach combines the "bandwidth reservation" and "degradation scheme" approaches into a unified whole, allowing us to provide this QoS. The 'bandwidth reserve system' made guaranteed that different services got dedicated bandwidth. As soon as a new call request is received and all available channels in a given class are in use, we employ an 'adaptive degradation strategy' in which the assigned bandwidth of each channel is significantly lowered and additional channels are generated and allocated to the new call request. The integration of these methods with CAC has boosted bandwidth availability, lowered blocking and dropping rates, and improved bandwidth utilization for specific categories of committed QoS.

[18] When it comes to mobile apps, including voice over internet protocol (VoIP), live gaming, and video streaming, there is a broad variety of quality-of-service requirements, ranging from low latency to high throughput. It is very necessary to have a comprehensive grasp of the expected performance of the network in-order to optimize quality of the network that end-users find themselves experiencing. The quality of the service that is actually given is contingent upon a great number of factors, including the network operator and the technologies that are available to the user. The vast majority of measurements taken from cellular networks, on other hand, do not take-into account the influence that network management and configuration have on performance. As result, purpose of this-research is to discover and comprehend the elements that contribute to unpredictability of mobile network performance. This is accomplished by discussing big dataset of measurements taken from cellular networks. The results of testing carried out on a 4G cellular network in Germany indicate that the decisions made regarding management and setup have a considerable impact on actual performance. It has-been shown that the affiliation of mobile device with a point of presence (Pop) in the network of operator has a substantial impact on performance of the transmission from beginning to finish. In-order to construct a model that makes use of data that we have, we use Markov chain and machine learning methods. This model is then used to anticipate the Pop assignment and RTT that will follow. The results of more than 57% of the measurements indicate an-increase in RTT that ranges from 58% to 73% when compared to the ideal performance. It is consistent with this theory as the results of monitoring the response and page load

times of notable websites show that there is a median rise of forty percent between the website with the worst performance and the website with the greatest performance.

[19] A higher level of service quality and extensive signal coverage are two characteristics that are shared by all wireless mobile infrastructures that been built. As technology continues to progress, there is-an increasing need for dependable mobile services. The purpose of this-article is to investigate performance of a cluster of 27 base stations for a wireless mobile network by using a call quality and driving test approach. Additionally, the paper advises that the system should be continuously optimized as the network grows stronger. Tuning base station resulted in an-improvement in performance, as assessed by Key Performance Indicators (KPIs), when compared to the states that existed before & after the tuning. A call attempt, percentage of successful calls, the voice quality index, the signal received, and the signal quality A concise summary of the situation The trend of wireless mobile architecture has seen significant changes throughout the years as a result of the ever- increasing requirements of a population that spans the whole planet. In an attempt to improve quality of service, mobile carriers and telecoms providers have, throughout the course of time, deployed pilot equipment, commissioned it, and then deactivated it depending on performance tests. When conducting an analysis of overall performance, it is essential to-take into consideration not only Key Performance Indicators (KPIs) of every component of telecommunications infrastructure, but also the impact of topography and the rate of congestion on mobile networks. As a consequence of the fact that worldwide linkages are dependent on an efficient wireless mobile network, there-is an urgent need to improve quality of service via improved planning, equipment tuning, or switching.

[20] the ever-increasing demand for over-the-air multimedia services has caused the research community to become very active in field of wireless multimedia networks. The Call-Admission Control (CAC) method is an efficient strategy that helps to support wide variety of integrated services that have certain Quality-of Service (QoS) needs. The CAC is responsible for regulating network access as one of responsibilities of resource management. This is done in-order to ensure that the supply of quality service is maintained. There are number of factors that contribute to complexity of the CAC selection process, including user mobility, limited radio spectrum, and

multimedia traffic characteristics. Within the scope of this study, we provide a secure-aware CAC solution for cellular wireless networks that follows the fuzzy logic approach. An evaluation of the suggested approach is carried out with the help of our innovative Fuzzy CAC Simulator (FCACS). We were able to show the great behavior of the CAC method that was proposed by modeling its performance and assessing its performance.

[21] In cellular networks, call admission control, often known as CAC, is a mechanism for managing radio resources that aims to offer mobile consumers with a grade of service (GoS) and quality of service (QoS) that is equitable. GoS refers to possibility of a new call request being denied, while QoS refers to chance of a decrease in quality-of communication. Both of these terms are often used interchangeably. Keeping in mind basic challenges that are-associated with cellular networks, such as coverage, capacity, throughput, the variable quality of service requirements of mobile users, and risk of blockage, this research presents an-overview of many methodologies that are used for CAC. With the goal of shedding light on their applicability in a homogeneous/heterogeneous traffic class, single/multi-cell environment in the uplink direction of a cellular CDMA network, we will attempt to evaluate & contrast performance of these approaches, taking into account the few criteria that are being discussed here.

[22] Call admission control (CAC) is a challenging topic to discuss when it comes to the provision of quality of service (QoS) in communication systems for mobile multimedia networks. Access to the network may be restricted using a mechanism known as Capital Access Control (CAC), which is based on resources that are currently accessible. If there are sufficient idle resources to meet the quality-of-service requirements of the incoming call without affecting the quality of service for calls that have already been authorized, then the call may be allowed to proceed. In such case, it will be rejected. The purpose of this-article is to provide an-overview of numerous CAC approaches that are used inside of mobile multimedia networks. Soft computing approaches, such as genetic algorithms, fuzzy logic, and artificial neural networks, are used in the implementation of these particular systems. Soft computing allows for the modification of a great deal of the components that are employed in mobile multimedia networks. In order to improve of the CAC techniques that are now in

use, our goal is to evaluate and compare the parts of soft computing that are the most successful in relation to mobile multimedia networks. Furthermore, this study investigates the potential that has not yetbeen fully realized in artificial-neural networks, fuzzy logic, and genetic algorithms, as well as future implications of-these technologies. The following names are interchangeable: genetic algorithm (GA), fuzzy logic (FL), artificial neural network (ANN), soft computing (SC), and call admission control (CAC). Genetic algorithms are used to find solutions to problems.

[23] recently, many forms of urban mobility have inspired examinations of the effectiveness of mobile data networks from a number of perspectives. These evaluations have included TCP/IP protocols, comparisons of WIFI, and even satellite communication. When it comes to circumstances that include high-speed transit on a scale that encompasses a number of cities and regions, however, the conclusion is still under investigation. In order to fill this void, we are conducting a comprehensive measurement analysis on the operation of mobile data networks when driving at high speeds (at least 300 kilometers per hour). The China Railway High-speed (CRH) network is the largest commercial high-speed railway network in the world, and this speed is currently regarded to be the standard. In-order to get things started, we will present a high-level review of performance of TCP across LTE networks. What we have discovered is that it is feasible to get a very excellent throughput when the circumstances are high-speed mobility. As opposed to the stationary and moving (100 km/h) scenarios, the throughput and RTT are much lower and exhibit a significant amount of variation. Next, we go further into the wireless channel and handoff, two crucial aspects of performance that need to-be taken into mind. In-addition to the Transmission Control Protocol (TCP), our study on these characteristics should be useful for certain other upper-layer protocols.

[24] through the optimization of the use of assigned channels in comparison to the traffic that is given, call admission-control (CAC) guarantees that the required-quality of service (QoS) is maintained. Inter-cell interference (ICI) makes it difficult to deliver quality of service to users at the cell edge when there are few cell resources available. This makes it difficult to provide quality service. The ICI mitigation approach identified as "Soft Frequency Reuse" governs the manner in which users share the resources that are available to them. Cutoff Priority (CP), Uniform Fractional Guard Channel

(UFGC), Limited Fractional Guard Channel (LFGC), and New Call Bounding (NCB) are the four CAC methods that are compared and contrasted in this research via queuing analysis. Also, the effect of each scenario at the cell boundary is investigated. Both of these aspects serve as the foundation for the comparison. The first criterion guarantees that a specific level of service is provided to customers who have been accepted, while simultaneously maximizing income. The second measure determines the bare minimum of radio resources that are required to place stringent constraints on the chance of dropping and blocking. In order to compare the four techniques various different situations involving new and handover-call arrival rates are used.

[25] the provision of quality of service (QoS) is an important-component of any system that makes use of several types of communications media. In wireless systems, it is a more challenging job to provide quality of service requirements for different-types of traffic. This is due to fact that two performance metrics—the risk of losing a handover call and the likelihood of blocking a new connection—must be reduced simultaneously. Because the quality of service (QoS) standards for non-real-time traffic are less stringent than those for real-time traffic, it is possible that more calls may be permitted if bandwidth were freed up from approved calls for non-real-time traffic. In situations when amount of released bandwidth that is used-to handle handover calls is larger than amount of released bandwidth that is utilized for new calls, the likelihood of dropping a handover call is lower than the likelihood of blocking a new call. Within the scope of this investigation, we provide an efficient method for the regulation of call admittance for calls that are not in real time by using an adaptive multi-level bandwidth-attribution system. The approach not only increases the amount of bandwidth that is used, but it also reduces the risk that calls would be dropped simultaneously. The numerical results reveal that the recommended approach has the potential to achieve a minimum handover call dropping probability without sacrificing the use of bandwidth.

[26] the provision of quality of service (QoS) is very important for any system that makes use of several types of media. As a result two performance metrics—the chance of losing a handover call and the possibility of blocking a new call—must be reduced simultaneously, the job of providing support for quality-of-

service requirements for different types-of traffic is more challenging in wireless systems. Because the quality-of service (QoS) standards for non-real-time traffic-are less stringent-than those for real-time traffic, it is possible that more calls may be permitted if bandwidth were freed up from the non-real-time traffic that was approved. In the event that the released bandwidth that is used-to handle handover calls is-more than released bandwidth that is utilized for new calls, likelihood of dropping a handover call is lower than likelihood of blocking a new call. An efficient call admission control method for non-real-time calls is presented in this work by use of an adaptive multi-level bandwidth-allocation system with which we-propose a solution. Furthermore, the strategy reduces probability of calls being dropped, in addition to increasing the amount of bandwidth that is used. The numerical data reveal that the recommended approach has the potential to achieve a reduced handover call dropping probability without decreasing amount of bandwidth that is-being used.

[27] Extensive coverage is provided in this-chapter on the many methods that may-be used to regulate which calls are permitted to be accepted-by mobile cellular networks. The following is a quick review of cellular technology, followed by discussion of the many techniques to call admission control that have-been developed by a variety of research organizations. Call queuing techniques, channel borrowing schemes, network implicitness and predictiveness, call priority, and other network features have-been taken into-consideration in process of introducing solutions for call admission management in a variety of network scenarios. The control of call admittance via use of soft computing technologies is shown. The artificial neural-networks, evolutionary-algorithms, fuzzy relational method, & particle-swarm optimization are some of approaches that fall under this category.

[28] everyone who is engaged, including the suppliers of network services, has to have a complete and accurate understanding of operation of cellular networks. Specifically, they are seeking for statistic that-assesses how well a network operates when customers are-actively engaged with their device. This metric would be implemented in context of network. Measurements of this kind are difficult to obtain because of many factors, such-as time and the physical environment that have an effect on the operation of cellular networks. This document has been-updated with two new items. In order to begin, we conduct large-scale measurement research

utilizing data obtained from a major cellular carrier in addition to hundreds of controlled experiments. This provides us with the opportunity to get better understanding of the issues that arise while doing in-context measurements. It is necessary to measure devices that (i) have recently interacted with the network, (ii) remain in the same macro-environment (for example, indoors and stationary) and, in certain instances, the same micro-environment (for example, in the user's hand) between two measurements, and (iii) do not generate a significant amount of user-generated traffic at the moment. These are the criteria that we have found to be necessary. As the second phase, it is-necessary to make use of-these significant discoveries in-order to construct and provide a prototype of an active measurement service for Android phones. Based on our analysis of 1650 data gathered from 12 volunteer devices, we found that the technique is capable of accurately deriving average throughput values that assess performance during times of active device and network activity.

[29] inside the context of this research, Voice over Internet Protocol (VoIP) applications operating inside an IEEE 802.11 Wireless Local Area Network (LAN) confront the difficulty of delivering Quality of Service (QoS). A strategy based on cognitive networks is what we recommend for the creation of a Call Admission Control (CAC) mechanism. The Bayesian Network (BN) is a probabilistic graphical model that represents the statistical correlations among the parameters of network. In this system, each user recalls critical data about their experience with network and utilizes those details to construct a Bayesian Network (BN). For this particular instance, we make use of BN in order to-make a prediction about quality of the phone conversation based on conditions that exist at the Link Layer. We make direct use of these predictions of the existing and future values of the supplied quality of service in order to develop the cognitive CAC scheme, which outperforms the most advanced CAC techniques in a test conducted in the real world.

[30] Guaranteed Quality-of Service (QoS) is of highest importance in any network; however, it-is of ultimate value in NGN settings that allow integrated services to be delivered across a shared IP transport network. Call Admission Control (CAC) approaches are the means by which quality of-service (QoS) is really provided to class-based services in a proactive manner. On other hand, when it comes-to autonomous CAC, machine learning techniques are chosen over analytical approaches. This is due

to the fact that NGN is characterized by its complexity, scalability, and dynamic nature. The purpose of this investigation is to assess the effectiveness of two techniques for modeling network behavior and predicting quality-of-service metrics that the CAC algorithm may use. These techniques are known as Bayesian Networks (BN) and Neural Networks (NN). With the help of this strategy, it is much simpler to-determine the optimal size for training a model in-order to provide accurate predictions. This comparison of performance is based on-number of tests that were-carried out in the simulated network that Opnet provides. This study provides light on the qualities and capabilities of NN and BN models, which may be utilized to improve CAC deployments. The findings of this comparison provide light on these traits and capabilities.

[31] the amount of radio frequency spectrum that is currently available to wireless systems is limited, which limits their capacity to handle the anticipated increase in traffic load and broadband services. However, it-is believed that mobile cellular networks would be-able to handle multiple services while still maintaining a certain level of service quality (QoS). Call admission control (CAC), which regulates who may access the network, is one of functions that resource management is responsible for. This is done to ensure that-quality of service that is provided is maintained. In spite of this, selection of CAC is a very difficult issue to solve because of mobility of users, limited radio spectrum, and the peculiarities of multimedia traffic. Our prior study included a comparison between the performance of a fuzzy-based CAC system that we showed and that of the shadow cluster concept (SCC) that we had previously developed. In this-section, we build upon the work that we have done in past by taking into consideration the significance of the ongoing connections. For the purpose of evaluating the performance of the recommended system, we make use of simulations and compare its performance to that of our prior work. Based on results of the performance evaluation, the system that was recommended demonstrates outstanding-behavior in terms of preserving quality of service of continuous connections.

[32] WiMAX, which stands-for global interoperability for microwave access, is one-of the possible solutions for last-mile Internet connection. use of this would be particularly beneficial in locations that do not-have wired infrastructures. Call admission control, often known as CAC, is used- in WiMAX networks in- order to

effectively handle variety of traffic loads and prevent the network from being overloaded. purpose of this-research is to propose a two-dimensional CAC design in order to meet number of features that are-associated with WiMAX networks. The 2-D uplink and downlink WiMAX CAC challenges are-separated into two-distinct 1-D problems in-order to facilitate design of the 1-D CAC optimization. This allows us to achieve more precision. During this optimization process, both requirements of service providers and those of consumers are-taken into account. As-part of our efforts to find solution to optimization problem, we devise a revenue policy that is-not only equitable but also restricted in its usefulness, and we also implement an algorithm that approximates this policy. Simulation data are shown in order to-demonstrate that the WiMAX CAC approach that was described is effective.

[33] A significant amount of reliance is placed on call admission management in wireless networks in order to guarantee a certain level of service. Due to limited and unpredictable resources of the network, as well-as the mobility of the users, the process of building call admission control algorithms for mobile cellular networks is extremely challenging. This article provides a summary of cellular network admission control systems as well as research that is currently being conducted in this area. A complete review and analysis of the various call admission control mechanisms that are currently in use is what we want to deliver. The flexibility of traffic, distributed and local control, and deterministic and stochastic assurances are some of the criteria that we use to classify these systems. Furthermore, we provide a fundamental understanding of modeling and analysis to assist in appreciating the effectiveness and performance of cellular network admission control strategies. This is our contribution to the field. We describe and assess number of different admission control mechanisms depending-on the degree of difficulty and effectiveness they exhibit. Handoff prioritization is something that all of these different systems have in common with one another. In-this article, we present an overview of many different-strategies that have been recommended to accomplish handoff prioritization. Our primary focus is on reservation systems. Additionally, optimum and near-optimal reservation algorithms are shown and discussed in this article. A high-level assessment of more key schemes is also provided by us. These schemes include those designed for hierarchical systems and multi-service networks, as well as extensive knowledge schemes and pricing-based call admission control algorithms. Before coming to a conclusion, the essay analyzes the current

research environment and draws attention to a few of the most significant challenges affecting call admission control for future cellular networks.

[34] One of most important aspects of mobile networks is called Call Admission Control, or CAC for short. A significant amount of research has been conducted on UMTS and GSM/GPRS systems that mix voice and data transmission. Despite this, the majority of CAC models and wireless communication described in the literature make use of a one-dimensional Markov chain, which is often based on voice conversations. This is done-in order to reduce amount of state space that the chain occupies. There is another issue in the research, which is that they do not synchronize mobile devices and servers. Within the scope of this paper, we want to evaluate a CAC strategy that takes into consideration voice connections, synchronous and asynchronous data connections, and each of these types of connections' performance. For purpose of illustrating this method, a multi-dimensional Markov chain in which the state space is quite extensive might be used. Consequently, we propose use of stochastic well- formed Petri Nets (SWN) in order to describe interaction of the system, which consists of number of mobiles, gateways, cells, and servers. For purpose of carrying out performance measurements, we make use of symbolic simulation.

[35] the first thing that we do is introduce a brand-new continuous action-set learning automaton. After that, we conduct a theoretical investigation into the properties of its convergence & show that it is capable of reaching the optimal action. In the next step, we provide a self-learning call admission approach for cellular mobile networks. This method is designed to-reduce the blocking probability of incoming calls while simultaneously being bound by the dropping chance of handoff calls. The learning automaton that was proposed is used-in this instructional method. According to results of the simulation, performance of our proposed method is comparable to that of the limited fractional guard channel algorithm, which necessitates that we have prior knowledge of all the features of the traffic.

[36] in context of this study, we began by constructing a unique continuous action- set learning automaton. Subsequently, we carried out a theoretical examination of the characteristics of its convergence, and finally, we demonstrated that it converges to the optimal action. After that, we provide a strategy for the admittance of calls that is both adaptive and autonomous for use in cellular mobile networks. While sticking to the

constraint on the dropping probability of handoff calls, this method takes advantage of the recommended learning automaton to minimize the blocking likelihood of incoming calls. This is accomplished while maintaining integrity with the limitation. As result of the close connection that exists-between performance of the suggested algorithm and the performance of limited fractional guard channel approach, it is-necessary for us to know all of the traffic characteristics in advance. Based on outcomes of simulation, it seems that this association does in fact exist.

[37] within the framework of multi-service wireless cellular networks, the problem of call admission control is being addressed in this-study that is now being conducted. The majority of research that has been-done in the past on call admission control has used a static strategy that is founded on a separate guard channel policy. At this point in time, we are of the view that a dynamic approach is required in-order to offer the requisite service assurance as well as essential service differentiation for the various types of traffic. Specifically, this is due to fact that the traffic behavior in multi- service wireless cellular networks is very dynamic. We focus on the performance of the connection level and offer a stable dynamic call admission (SDCA) approach that is capable of effectively handling mixed forms of traffic. This work is part of scope of work that we are doing. First, it must ensure that quality of service (QoS) promise is enforced on the dropping probabilities of all traffic; second, it must ensure that different classes of traffic are treated fairly; and third, it must ensure that stability is maintained throughout a wide range of traffic rates. These are the three primary goals that the proposed SDCA aims to accomplish. Furthermore, the results of the simulation provide compelling evidence in support of its performance.

[38] the basis for the creation of novel call admission control (CAC) algorithms is provided by cellular neural networks, which are-used in this scientific study. These algorithms-are able to achieve high network utilization, which is crucial component in process of sustaining quality-of service (QoS) communication across packet- switched networks. This is accomplished by executing CAC in real-time, which-allows them to achieve this utilization. In area of access technology, which is concerned with the supply of services to a subscriber population connected to Internet via an access module, the solutions that have-been supplied are of essential significance. Reason being, service supply is at heart of access technology. The only way to keep

the service quality up in this case is to restrict access to just those user settings that won't overload the access module. In this study, we model the CAC issue as a set separation problem and find the separation surface by comparing it to a training set. Consequently, CAC is transformed into an image processing problem: identifying a complicated admission pattern from a limited set of training points is the challenge. Due to CNNs' flexibility in adopting any propagation model to analyze complex patterns, CAC may be performed using CNNs. As a result, CNNs are able to study intricate patterns with relative ease. Finding the right template matrix that would lead to high network usage is crucial for overcoming the basic obstacle. Furthermore, three-dimensionally ordered separation surfaces may-also be handled using the method that has-been given. Consequently, in an average access situation, three types of traffic are present. One phone call over an asymmetric digital subscriber line and two types of Internet access make up these types of traffic. With the offered method, all three of these types of traffic may be controlled.

RESEARCH GAP

The use of artificial-intelligence (AI) to regulate which calls may be admitted to mobile networks is an important new area of study in the field of telecommunications. The necessity for effective call admission control systems is becoming more and more obvious as mobile networks adapt to support varied range of users and applications. There has-been lot of progress in mobile networking technology, but there is-still lot of unanswered questions about-how to use AI to improve call admission control. Unpredictability in user behavior and network circumstances, together with ever-changing nature of mobile networks, is one of main obstacles. It is-possible that conventional methods of call admission control, which depend on static thresholds or oversimplified rule-based techniques, will not be-able to adequately adjust to the ever-changing dynamics of network. By allowing intelligent decision-making and real- time analysis of network data, integrating AI methods like deep learning and machine learning presents a possible route for tackling this difficulty. Optimal network performance vs. guaranteed quality-of service (QoS) is another important but underexplored topic. While improving user experience and keeping up with rising demand both need increasing network capacity and throughput, doing so must not come at the expense of satisfying the quality-of-service requirements of current connections. A multidisciplinary study is needed to solve optimization challenge of designing

AI-powered call admission control algorithms that can adapt admission choices on the fly according to QoS measurements and network load.

Artificial intelligence (AI) call admission control systems also have substantial research hurdles when it-comes to scalability and implementation practicality. With ability to connect millions of users in different parts of world at once, mobile networks are capable of handling very large data loads. To make AI work in real world, we need algorithms that can handle massive-amounts of data in real time with little computing cost. To make-sure AI-powered solutions operate in real world, we need to think about things like how-much energy they need and if they're compatible with our current network setup.

CHAPTER 3
MOBILITY-BASED CAC AND RESOURCE ESTIMATION MODEL USING ANN

3.1 BACKGROUND

Because mobile users (MUs) are free to roam anywhere in a wireless environment, mobility prediction is crucial in mobile communication for pinpointing the precise location of MUs so that resources can be allocated efficiently to meet their needs and quality of-service (QoS). In order to achieve next-generation mobile network speeds, widespread high-quality speech, abundant large bandwidth, and minimal delays, mobility is seen as a primary goal in mobile multimedia networks.

The need for network services is always growing, and mobile communication technologies have also seen enormous expansion in the last several decades to accommodate this demand. There are mainly two types of mobility: radio mobility and network mobility. In contrast to network mobility, which focuses on management of mobile user locations, radio mobility mainly pertains to the call handoff process. Whether it's a cell, an area, or a section of a Mobile Switching Center (MSC), the network must almost likely locate the mobile user and then route the call to that user.

A "handoff" or "handover" is the primary component that regulates movement. The handoff occurs when the MN begins to receive data packets from the new base station, which occurs after mobility detection. In most cases, a handoff will be executed if a neighboring target cell provides a better signal quality compared to current serving cell. However, one of most fundamental problems in a mobile network occurs when a mobile user unit (MU) moves from its current cell's inclusion area to another cell's inclusion area and there aren't enough resources to handle incoming handoff calls. The call is dropped in this-case, which is much worse than call blocking. As a result, each cell sets aside a small portion of the resource specifically for MU handoff. While it's possible that no MU will use the reserved resources, the system for reserving them should be structured to ensure that both new and handoff calls continue to have a high quality of service. The procedures for determining handoff decisions have been thoroughly discussed in relation to cellular and mobile networks.

There been a plethora of solutions that focus on geological areas that can enable network establishment, which allows for smooth mobility prediction assistance in

recent years. Every one of these mobility prediction methods is one-of-a-kind and was developed to address a specific problem. Location, user movement history, mobility patterns, dwell times, and combinations of these factors were the basis for many earlier suggested techniques. For systematic Call Admission Control (CAC), approaches based on user mobility were-used to collect mobility-related data. When it comes-to managing the precise position of MUs, the most fundamental and well-established methods for mobility prediction are the Fluid Flow Model, the Random Walk Model, the Markovian Model, and the Gravity Model. As result of the MUs' daily activities in each visited cell, a movement-based mobility prediction approach was suggested utilizing the Hidden Markov Model. The wireless network also made use of the Hidden Markov Model to pinpoint the MUs' locations according to users' past movements over vast geographical and temporal scales.

Choosing the right model and parameters is essential for developing a mobile prediction algorithm that improves handoff performance via widespread forecast accuracy. This chapter's suggested technique makes use of MU profile data such as mobile serial number, mobile number, MSC ID, BS ID, anticipated entrance time, date, and visit count. Not only does this user data help with MN movement prediction, but it also helps with handoff resource allocation. A CAC and a strategy for reserving resources are required to fix the aforementioned problem and keep quality of service offering in place.

In-order to minimize CDP and CBP via optimal usage of resources, this chapter presents development of a mobility-based CAC and resource estimate model that-utilizes artificial-neural networks (ANN). Finding the future handoff position of user mobility in-order to pick the suitable BS using an EBP neural network is the study target of this chapter. The queuing model assigns resources to users according to their predicted mobility or the location of the handoff. By allocating sufficient resources, model was able to manage handoff calls, which improved mobility accuracy and resource consumption while decreasing CDP.

3.2 PREDICTION OF MOBILITY

With a mobile-multimedia network, users may access their services whenever and wherever they choose. In order-to provide high-quality services "anywhere anytime," network system needs mobility management to maintain track of and update

Location-information of MUs. Two main categories of mobility-prediction are

"Location Management" and "Handoff Management".

3.2.1 MOBILITY OR HANDOFF MANAGEMENT

Typical topics covered by mobility-or handoff management include intersystem handoffs, user-verification, and automated roaming. A user may access services outside of their home network service provider's territory with the help of automatic roaming, which involves a series of network operations. These features are pre-programmed and do not need any manual-intervention from the user. There are few ways to classify the autonomous roaming operations: HLR, VLR, Mobile-User State Management, and Mobile User-Location Management. Here, the validation process necessitates validating the network system's MUs, which means verifying the identification of each MU. One of the most fundamental features of mobile-network that allows users to roam around is handoff. The handoff feature makes it possible to maintain a connection with a user who is moving. However, a major and complex issue in mobile-networks is controlling handoff components.

3.2.2 LOCATION MANAGEMENT

Methods for managing the user's location are conditional on their-movement and the characteristics of their approaching call rate. To-determine the precise whereabouts of a mobile unit, one employs location management. The incoming call is directed by network by checking the locations of MU using Location Update (LU) mechanism. Each and every one-of those cells containing mobile-nodes gets a paging message from the paging method. The LU cost and paging cost are not mutually exclusive. Since paging is done across a small zone, even if the LU-cost is large, paging cost will be modest. On the other side, paging covers a larger area, therefore even with a low LU cost, the cost will be considerable. Both periodic LU and LU on cell-boundary- crossing are used-in location management. In-order to solve the problems with mobility prediction, this method used two-kinds of registers. Whenever an MN moves-to a new cell, it must first register with VLR. A VLR keeps track of the profile of MU when it transitions from one cell-coverage location to another, while an HLR holds network user profile for specific network.

3.3 EXPLANATION OF PROBLEM

Think about a situation where an Access Point (AP) is linked to a MU. Some MUs may temporarily disconnect from their present AP (let's call it A_j) and then reconnect to a nearby AP (let's call it Ak) after a short while. By looking at past and future transitions, we may try to foretell when the MU will go from A_j to A_k. The system is unaware of anything else, such as the MU's transition from A_i to A_j. From A_i to A_j and A_j to A_k, the system is also aware of the likelihood of each transition. The algorithm uses this data to foretell when the MU will move from A_j to another nearby AP. These changes in trajectory could seem different for distinct MSs because of their unique-movement histories and the routes they've followed. Therefore, in-order to provide more precise forecasts, a more effective model is required.

In light of the above, this-chapter employs Error Back-propagation Neural-Network (EBP-NN)-model to make precise predictions about users' next movements; this allows the network to hopefully set aside-sufficient resources for handoffs to-reduce CDP & CBP.

3.4 ERROR BACKPROPAGATION NEURAL NETWORK

One use case for layered feed-forward neural-networks is Error Back-propagation Neural Network, or EBP-NN. This approach is a kind of supervised learning that uses a multi-layer configuration of artificial neurons to convey input signals "forward" and then propagate errors in the opposite way. By adjusting the weights, it accurately describes the input patterns. Various input, hidden, and output layers make up this multilayer feedforward network. Neurons in one layer are related with neurons in the layer below them via a weighted relationship. The gradient-descent approach is fundamental to the concept of EBP. The next step, after design, is training the network, and the difference between the goal and desirable outputs is called error. To fix this hidden layer mistake until network lea training data, EBP is used.

The network is-trained in three-stages,

I. Forward input signals

II. Process and propagate-error backward

III. Update weights

The EBP network's brilliant capacity for self-learning and organization makes it ideal for use in mobility prediction. main premise is-that it uses randomly selected input patterns to train network. first step is to create the neural networks, which involves deciding on the optimal layer and neuron counts as well as initializing the weights. In addition, learning algorithms decide how to train the networks after selecting a transfer function (e.g., a sigmoid or linear function) and calculating the error.

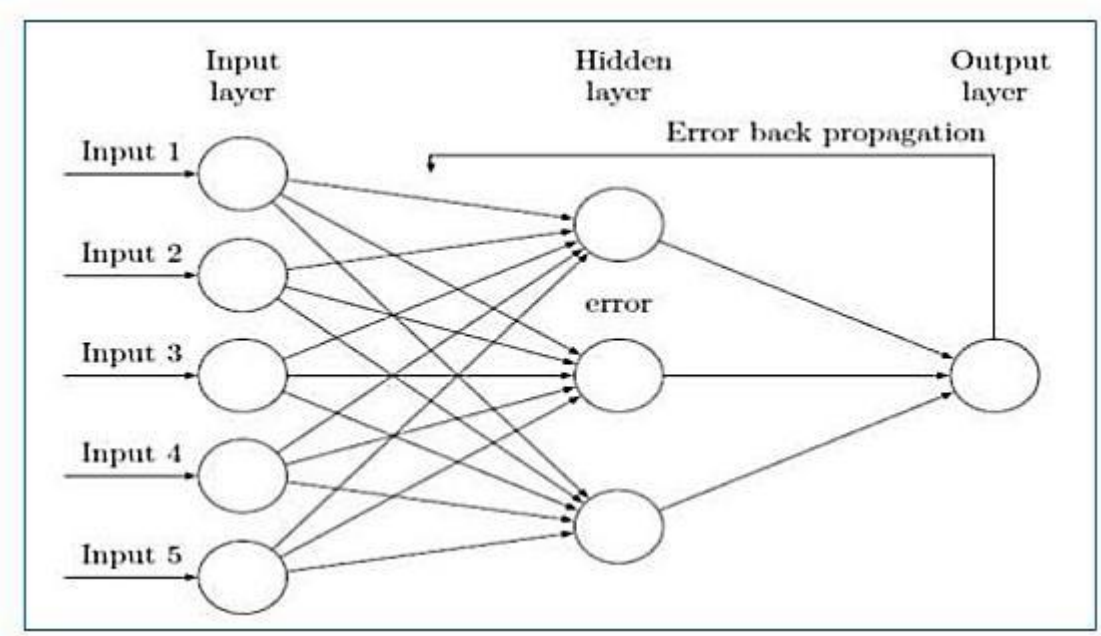


Figure 3. 1 Architecture of the Error Back-propagation Network

In addition, output is decided upon and patterns are expected as they go from input layer to output layer. The next step is to update weights among the different layers. next step is to verify that all layers' weights have been updated. If the estimated output differs from the expected result, we will calculate mean square-error for t hidden layers.

3.4.1 THE ALGORITHM OF ERROR BACK-PROPAGATION TRAINING

Step 1: Initialize the weights, which are typically chosen at random, and apply input to the network first.

Step 2: Perform a forward pass, which involves calculating output of each-neuron from the input-layer, through hidden layers, & finally to output layer.

Step 3: Calculate-difference between target output & desired output. Calculate

error (E) of input pattern (p) using the-following equation.

$$E(p) = \frac{1}{2}\sum_{i=1}^{n}\left(target(p) - output(p)\right)^2$$

Backward propagation (Weight updating)

Step 4: To get output-error for each neuron, use following equation if output deviates from the desired output.

δ_{output} = output (1 − output) (tager /output – output)

The "output (1-output)" term is-necessary for-Sigmoid Function /only for threshold neuron it would-be (target output– output).

Step 5: following equation is now-used to update all-weights from output layer to hidden layer.

$W_{n+1} = W_n + \eta\, \delta_{output} \times$ output hidden layer

Where $Wn+1$is new (trained) weight and Wn is initial weight. Where η is learning rate-that is lies-between 0-to 1.

Step 6: Weight modifications are-applied after each hidden layer neuron's mistake has been computed and delivered backwards to output layer. In-order to get error for each hidden-layer node, following equation is used.

δ_{hidden} = output (1 −/output) Σ δ_{output} ×

Wn+1 Where /Wn+1 is updated weights

Step 7: After-calculating error weights are updated at hidden layer using following equation

$$Wn{=}1Wn\ \eta\delta_{\text{hidden}}\ \text{outputi}_{\text{input layer}}$$

It should be noted that in Step 3, total cumulative-cycle error of the input-output mapping is calculated-by adding together all the continuous-output errors in whole

training set. After every iteration of the training set, the total error value for whole cycle is determined. The stages 2–7 of input pattern will be repeated-for each iteration, until output layer's Mean Square-Error (MSE) either minimizes or falls below the set number Emax, which may be anywhere from 0 to 1. following equation determines an error-for each training pattern:

$$E(MSE) = \sum E(p)$$

The training-cycle is completed, & terminate training session if E< Emax, otherwise initiate-new training cycle by-going to step 2.

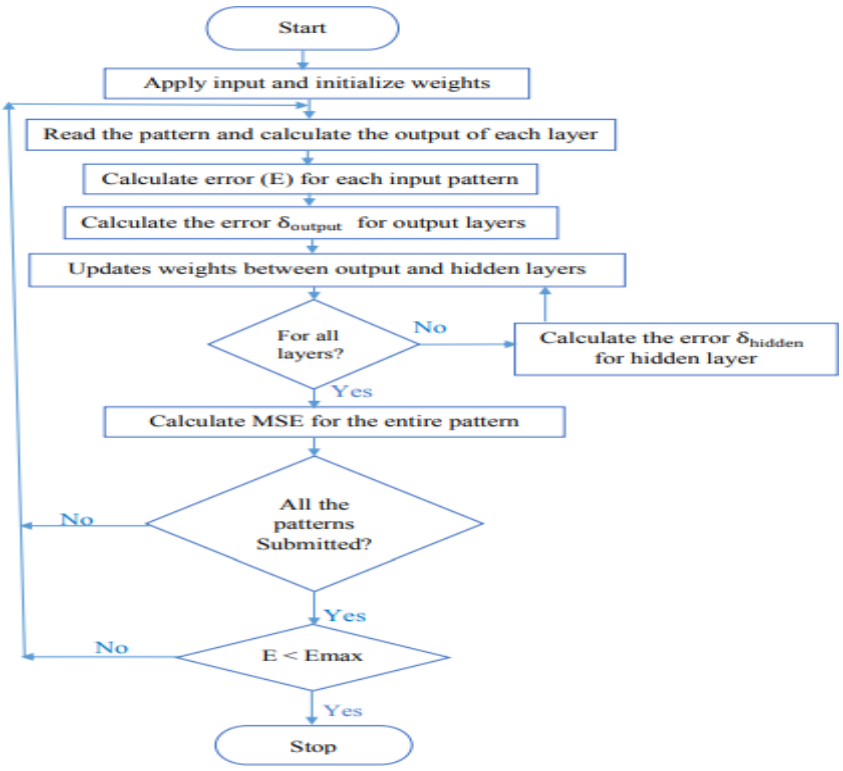


Figure 3. 2 Flowchart of Error Back-propagation

3.5 ENHANCING CALL ADMISSION-CONTROL AND RESOURCE ESTIMATION USING ANN: A MOBILITY-BASED APPROACH

Quality-of service (QoS) in mobile-multimedia networks relies heavily on CAC, which is also a major tactic for effective management of resources. In this context, it has been

used for the purpose of managing radio resources in accordance with user mobility or handoff. Allocation of resources is crucial when handoff is happening.

Consider a situation where each-Base Station (BS) is allocated total bandwidth of B unit for use in both incoming and outgoing calls. In addition, the bandwidth B is divided into the free bandwidth and the consumed bandwidth (Bb). Thereby, the whole bandwidth is

$$B = Bf + Bu$$

In comparison to new calls, handoff calls are often given more priority. Only a small fraction of available resources is set aside for handoff calls. Both new &handoff calls use the leftover resources (B-N) if there-are B available resources/bandwidth and N allocated for handoff calls. The likelihood of call dropping rises if there-are insufficient resources in cell where handoff happens. In-order to solve the problem of-handoff call drops, queuing model was created to provide services for both new & handoff -calls.

3.5.1 QUEUING MODEL FOR HANDOFF AND NEW CALLS

There-are following-steps followed by queuing-model as described-below

Step 1: Poisson-process is-used to analyze the patterns of call arrivals.

Step 2: The-queuing model states that handoff calls should be given greater priority depending on channel holding-time.

The channel holding-time TH-can be calculated by following formula.

$$\int_0^\infty \mathrm{e} - \mu Htdt = \int_0^\infty ((1 - \frac{\lambda n}{\lambda} FTHn(t) - \frac{\lambda \mathrm{n}}{\lambda} \mathrm{FTHh(t)dt}$$

Here FTHn(t) & FTHh(t) define-channel holding time-for new calls & handoff calls.

Step 3: In this-step, assumed-two kinds of -ueue one for-handoff calls (Qh) & second for new calls (Qn).

Step 4: B resources make up the BS. Both requests will be considered if the resource

is free; otherwise, the new request will be denied.

Step 5: Whenever a resource is unavailable,handoff calls are grouped together with the CHC limit, & new calls are grouped together with Qn. This only happens if the available resources-are less than (B-R) when the new-arrival calls are made. Once queue is filled, new calls may not be able to get through.

Step 6: The chance of a handoff being dropped is disregarded if Qh is large enough.

Step 7: When a user-moves from-one cell border to-another or call ends, queue is emptied.

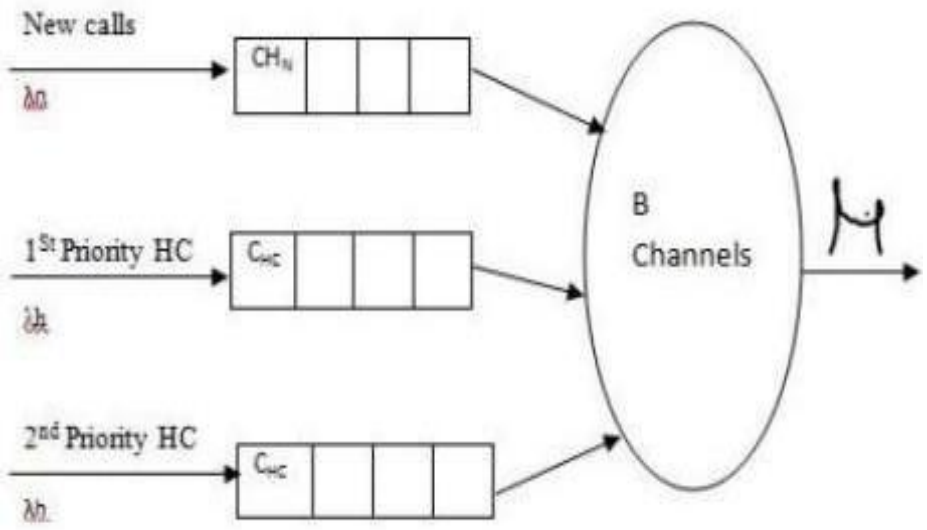


Figure 3. 3 Queuing Calls Model

3.5.2 MOBILITY-PREDICTION BASED RESOURCE ALLOCATION ALGORITHM

Step 1: Call-request

```
if ( Call_New)                    // For new calls
{
      if (Resource_Available)
```

```
            Accept new call
        else
            Block new calls
    }
    else if (handoff_calls)                    // For handoff calls
    {
      Check for dynamic reserved channels based on mobility prediction

        if (Resource_Available)
            Accept handoff calls
        else
            Put it into priority queue and wait for free resource availability
        if(Resource_Available)
            Allocate to high priority call and accept it.
        else
            Drop handoff calls
}
Else
{
Reject the call request
}
```

3.6 SIMULATION STUDY FOR EVALUATING-MOBILITY PREDICTION MODEL PERFORMANCE

Here we lay the groundwork for a simulation exercise that will-test how well the CAC schemes & mobility prediction model we introduced in the previous section work. During the simulation, an EBP-neural network is used to pinpoint the precise position of the MU. Subsequently, a resource allocation method based on a queuing model is put into place to distribute radio resources when the MU transitions across cells. Our method may decrease CDP and CBP while increasing resource consumption by not

only finding the MU's present position but also predicting the mobile user's future location.

The MATLAB software is-used to simulate the created plan. A-training data collection is created according to MU's instructions for the simulation.

This method uses the data from the HLR & VLR registers, as-shown in table 3.1, to make large-scale individual predictions.

Table 3. 1 Mobile Node Information Parameters

SERIAL NUMBER	MOBILE NUMBER	MSC ID	BS ID	EXPECTED ENTRY TIME	DATE	NO. OF VISIT

Predictions about mobility are made using this training set. A 2 square kilometer area is used for deployment of MN & cells in-order to forecast the MU's placement. Four MN are found in each cell. From one cell border to another, every MN follows a straight path.

To evaluate EBP's efficacy in a new setting, we simulated two distinct real-world settings (Linear and Random), with prediction accuracy and resource reserves serving as the model's core tenets.

In this section, we will go over the model that was chosen and how our suggested model compares to previous Hidden Markov Model-based mobility-based call-admission control schemes. (HMM).

3.6.1 TRAINING DATA SET FOR MOBILITY PREDICTION

For the purpose of mobility-prediction, this design utilizes the set D= {East, West, North, S o u t h , N o r t h -East, N o r t h -West, S o u t h -East, S o u t h -West} =

{1,2,3,4,31,32,41,42}. In this case, the topology makes use of EBP-neural networks to forecast mobility; these networks consist of an-input layer with-four neurons, two hidden-layers with six neurons-each, and an output-layer with twenty-one neurons. Each timeframe's cell visit is used to determine distance. Data from MUs' recorded directions during a random period of time and from MUs' historical records (table 3.2)

make up training set.

Table 3. 2 Training Dataset for Mobile User and Prediction Results

Ds1, Dr1	Ds2, Dr2	Ds3, Dr3	Ds4, Dr4	Output (Dr5, Ds5)
(1,2),	(1,42)	(4,2)	(1,4),	(1,2),
(1,42),	(4,2),	(1,4),	(1,2),	(3,31),
(4,2),	(1,4),	(1,2),	(1,31),	(1,2),
(1,4),	(1,2),	(2,31),	(1,2),	(4,4),
(1,2)	(1,31),	(1,2),	(4,4),	(1,2),
(1,31)	(1,2),	(4,4),	(1,2),	(2,41),
(1,2),	(4,4),	(3,2)	(1,41),	(1,1),
(4,4),	(1,2),	(1,41),	(1,1),	(1,3),
(1,2),	(1,41),	(1,1),	(1,3)	(1,3)
(1,41),	(1,1),	(1,3),	(4,1),	(1,42),
(1,1),	(1,3),	(4,1),	(1,42),	(4,1),
(1,3),	(4,1),	(1,42),	(4,1),	(2,1),
(4,1),	(1,42),	(4,1),	(2,1),	(2,41),
(1,42),	(4,1),	(2,1),	(1,41)	(1,4)
(4,1),	(2,1),	(1,41),	(1,4),	(1,4),
(2,1),	(1,41),	(1,4),	(1,4),	(1,4),

Each mobility pattern P is partitioned into two-sections as Dsj andDrj, where Dsj shows distance traveled by an MU at j^{th} time fraction andDrj, shows the possible future

Location-of an MU at j^{th} time interval. During-training stage as location of user is found, CAC-scheme will check-accessibility of radio-resources & make decision to admit-or deny calls. simulation result of proposed-model gives assurance of-keeping CDP and CBP-below threshold-value. Fig. 3.4 shows performance of model & mobility prediction of users.

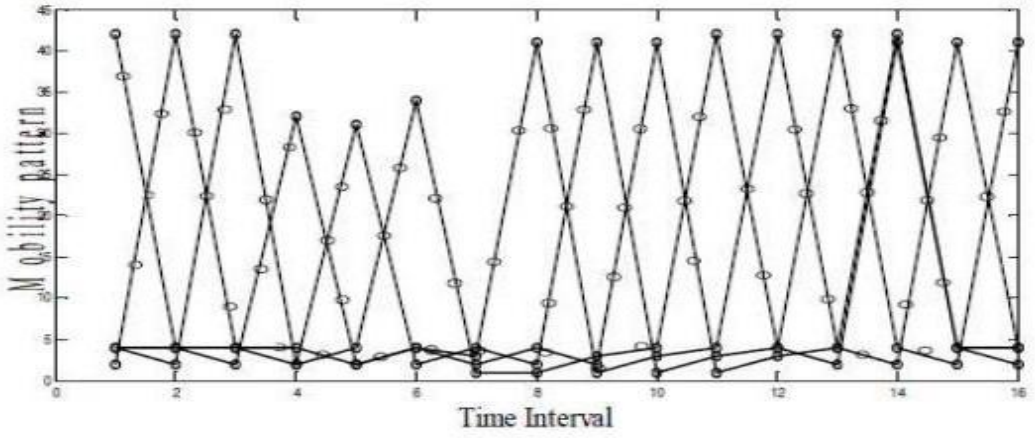


Figure 3. 4 System Performance Analysis & Mobility Prediction

Table 3. 3 Parameters of Simulation

Parameters	Details
Area Size	2 Sq. km.
Radius-of cell	600-meters
No-of cells	5
Area of-each cell	500 ×500-Meters
Number of-Channels	100
Call-holding time	25 sec to-125 sec
Call-arrival	Poisson-Process (λ)
Selection of mobility-pattern	Random/ Non-Random
Mobility Model	Random-Way Model

When checking the EBP model's performance, one of most important metrics is the accuracy of the predictions. A small number of mobile users' mobility accuracy is shown in Fig. 3.5. Enhancing mobility prediction capabilities with ongoing EBP training.

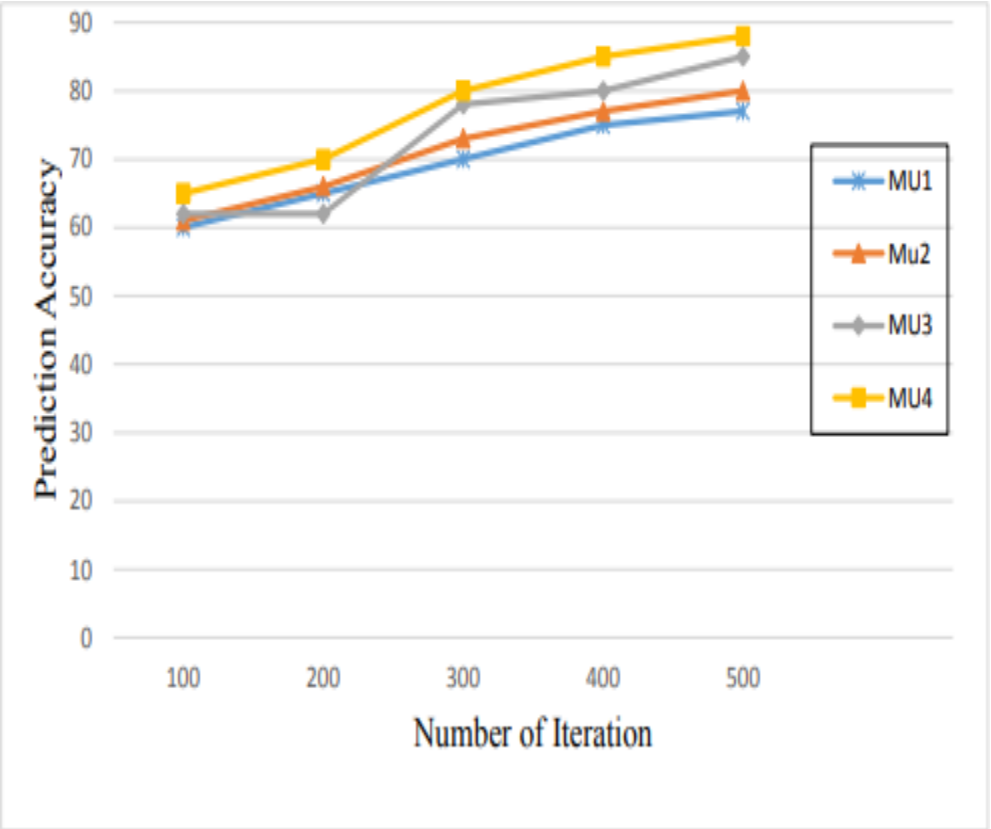


Figure 3. 5 Effect of Iterative Improvement of EBP on Prediction-Accuracy

Calculating the produced model's performance and comparing it to the HMM-model using a matrix including number of handoff-calls, handoff- failure rate, resource consumption, and system throughput is the next step.

Before a handoff happens, available resources in BS are calculated using prediction approach in the EBP algorithm. This results in fewer handoffs, as seen in Figure 3.6, when contrasted with the HMM-based prediction model. As seen in Figures 3.6 and 3.7, when contrasted with HMM method, number of handoffs is-reduced by 20% and the rate of handoff failure is lowered by 30%.

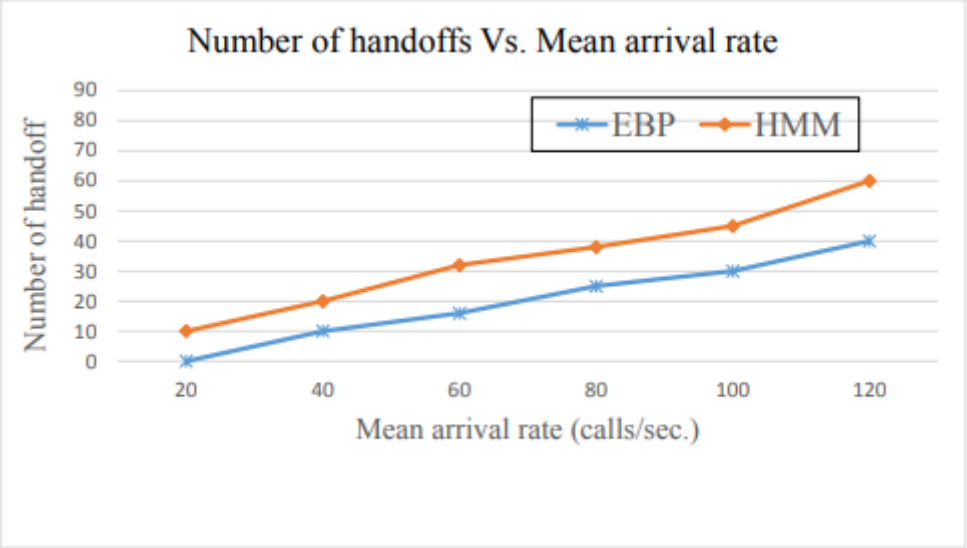


Figure 3. 6 Number of Handoff in-EBP

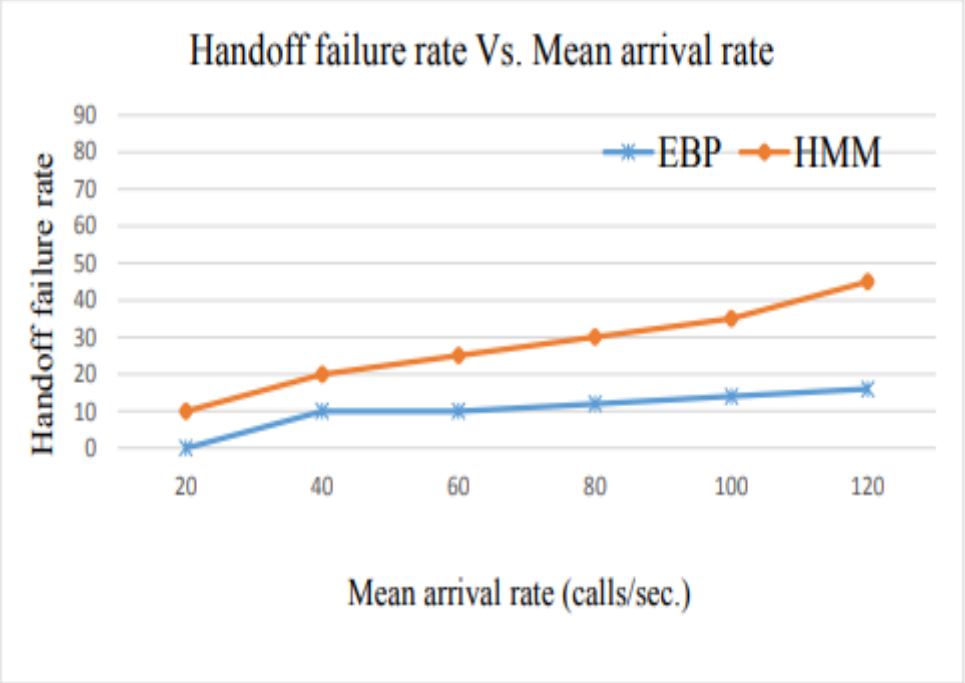


Figure 3. 7 Handoff Failure Rate in EBP

HMM-based prediction-algorithm outperforms the EBP-based method in terms of CBP, CDP, and resource usage (Fig. 3.8, 3.9, and 3.10). This methodology has the potential to boost resources by 15% while decreasing new CBP by 25% and CDP by 21%.

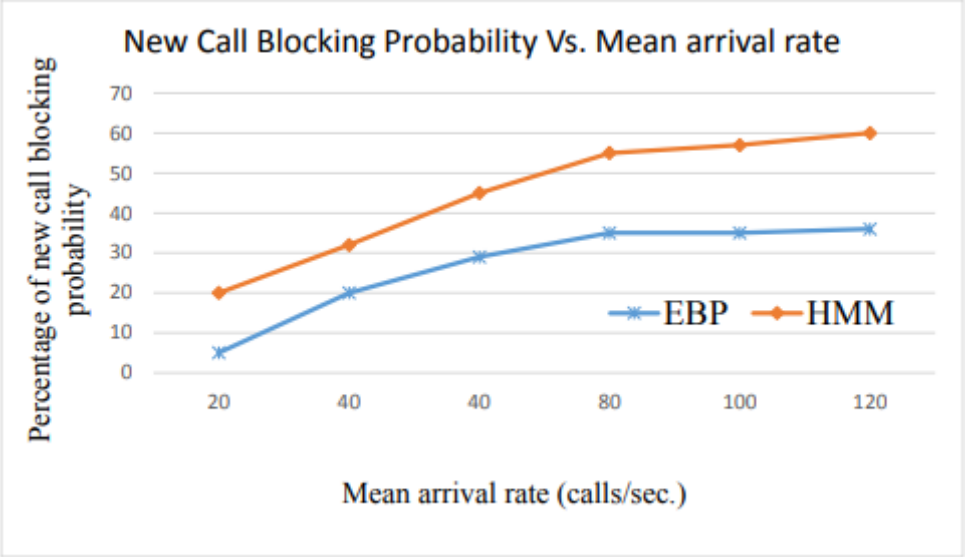


Figure 3. 8 Percentage of New-Call Blocking

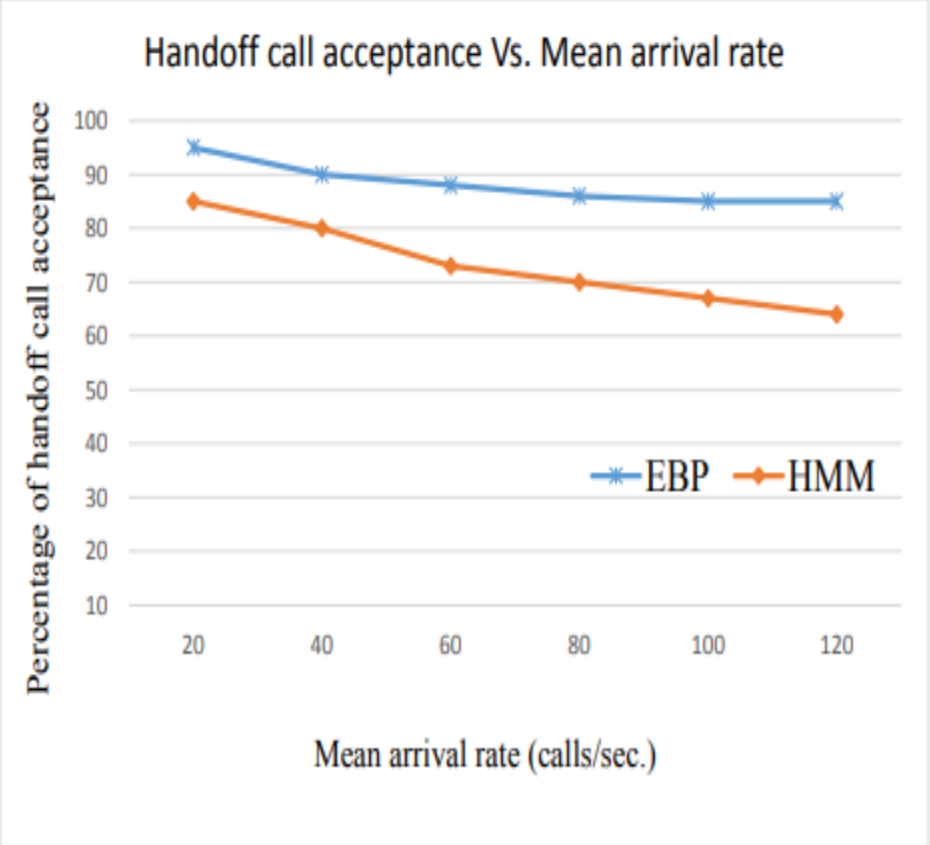


Figure 3. 9 Percentage of Handoff Call-Dropping

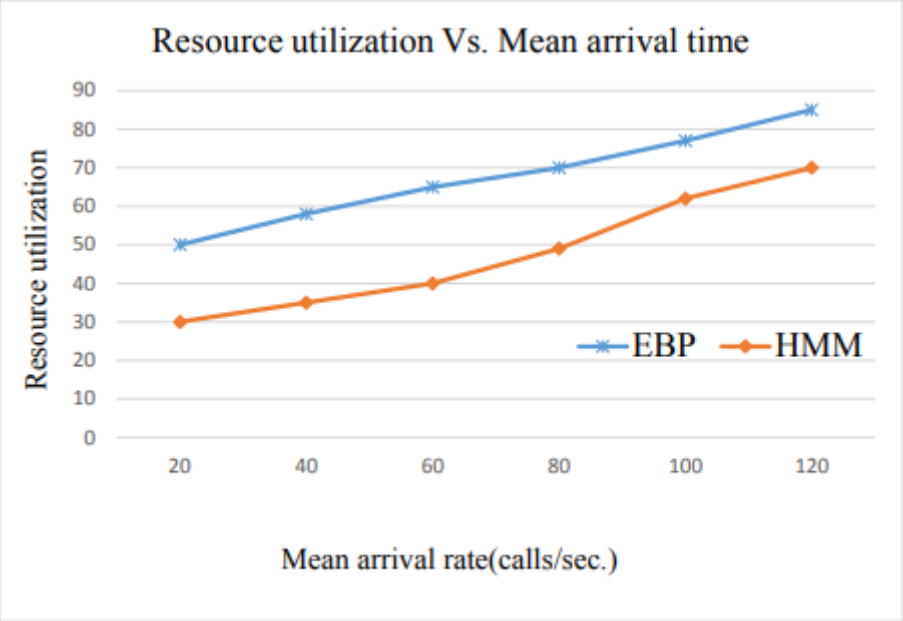


Figure 3. 10 Resource-Utilization by EPB

The simulation results suggest that, as-shown in Figure 3.11, throughput of the EBP-based-algorithm is 29% higher than that of the HMM-based methods.

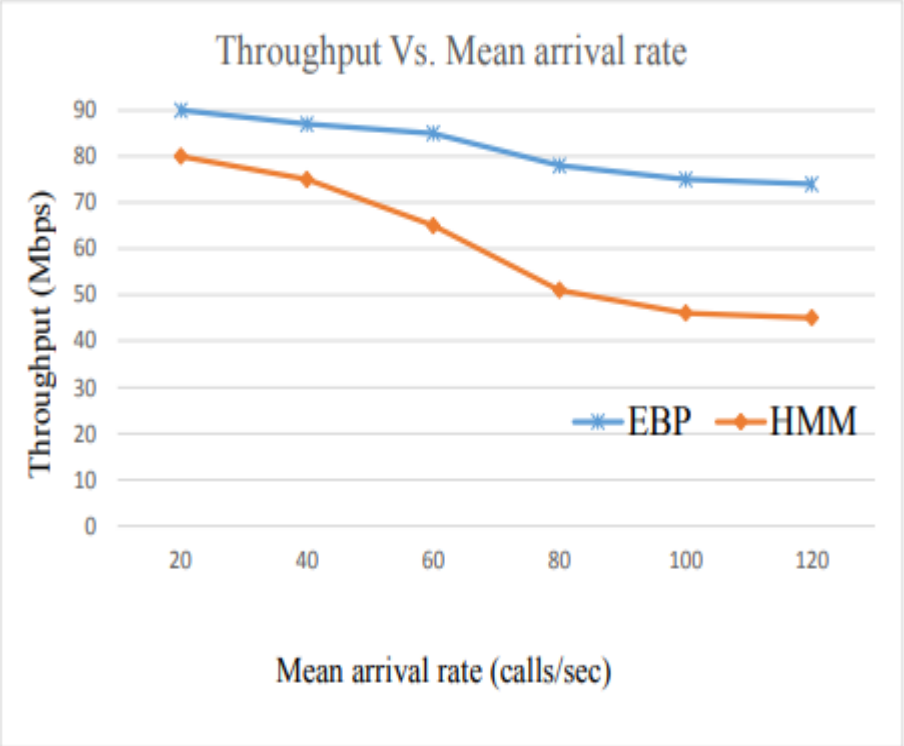


Figure 3. 11 Throughput-Analysis of the Model

Table 3. 4 Comparison of EBP Model & HMM Model

Mean arrival rate	No. Of handoff call		Handoff - call acceptance		New call - blocking		Resources Utilization		Throughput	
	EBP,	HMM,	EBP,	HMM,	EBP,	HMM,	EBP,	HMM,	EBP,	HMM,
20	0	10	95	85	5	20	50	30	90	80
40	10	20	90	80	20	32	58	35	87	75
60	16	32	88	73	29	45	65	40	85	65
80	25	38	86	70	35	55	70	49	78	51
100	30	45	85	67	35	57	77	62	75	46
120	40	60	85	64	36	60	85	70	74	45

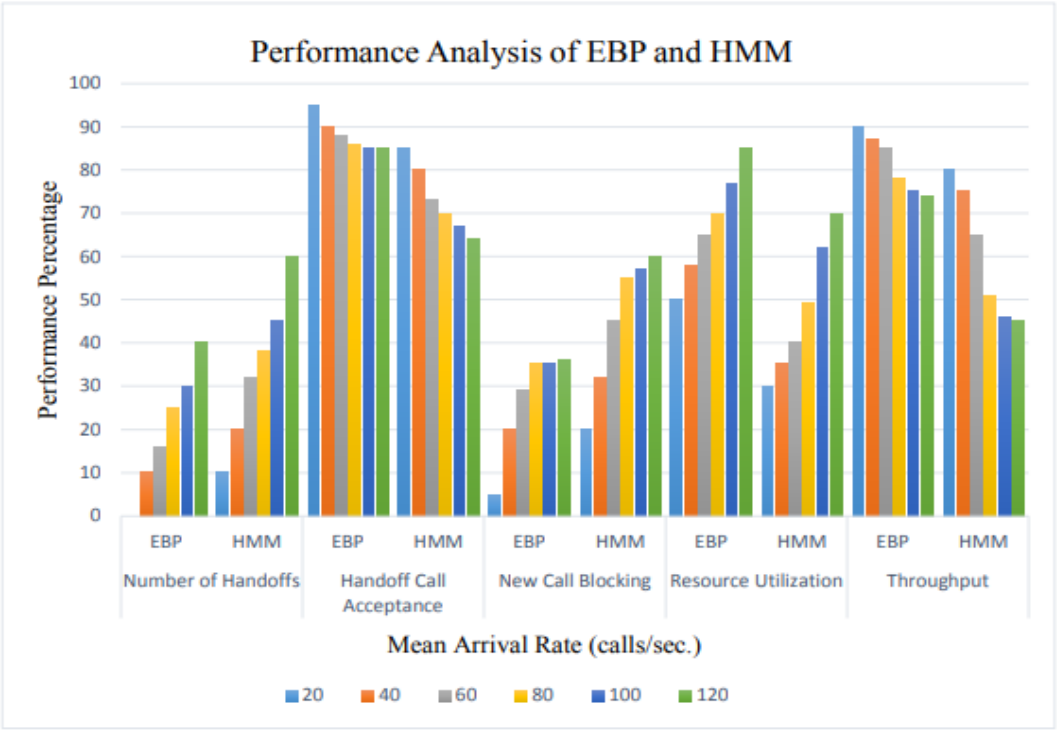


Figure 3. 12 Comparative Analysis of EBP Model & HMM Model

This paper proposes a system for estimating resources and controlling call admissions based on mobility. The efficient operation of wireless-communication relies heavily on mobility prediction. suggested model is able to precisely anticipate the user's future mobile locations by using Error Back-propagation predictor model-for mobility prediction. home base-station initiates handoff decision process when MU is likely to make a handoff, taking into account several-characteristics such as available-bandwidth and network load gathered, among others. Using this strategy, we have successfully predicted the movement of both single and multiple mobile nodes (MUs) in the network. The resource estimating technique was built utilizing queuing model based on-mobility prediction, which determines when and-next handoff would occur. Based on simulation results and-table 3.4, it-is clear-that proposed algorithm outperforms previous techniques. This is due to its high throughput, low number of handoffs, and optimal reduction of CDP & CBP.

CHAPTER 4
DYNAMIC CHANNEL ALLOCATION USING-HOPFIELD NEURAL NETWORKS-FOR CONFLICT- FREE CHANNEL MANAGEMENT

4.1 BACKGROUND

The interest in mobile communication and multimedia services has-been continuously growing in the past few years. Data transmission and communication between mobile devices and the mobile multimedia network's Base Station (BS) need a limited amount of useable bandwidth, which poses a substantial challenge to bandwidth planning in terms-of productivity. This is problem that can be explained with the term channel allocation. The goal of a channel allocation strategy is to allocate channels to cells to allow them to process the incoming traffic efficiently, while satisfying any constraints on the number of channels.

The problem-of optimum channel allocation has-become more important with the increasing demand for mobilecommunication services and the decreasing frequency spectrum. The optimization-problem has been proven to be Np complete. It has been solved using a number of heuristic methods, such as-Genetic Algorithms, Particle Swarm Optimization, and Neural Networks. From the review, it is possible-to conclude that there are several-researchers who have applied HNN in wireless communication.

Their least interference frequency allocation efforts-have been directed towards Fixed Channel Allocation (FCA) systems. A cell-model that was chosen at random has been used. To meet the demand without any conflict of channels, a new and efficient method is introduced in this chapter using Hopfield Neural Networks (HNN). The simulations showed that the HNN was able to reduce the call rejection ratio using four benchmark issues.

4.2 PROBLEM OF CHANNEL ALLOCATION

The Channel Allocation Problem (CAP) is the process of assigning a channel to a caller from a pool of available channels in a manner that satisfies the allocation matrix's constraints while minimizing interference overall.

4.2.1 CONSTRAINTS IN CAP

There are mainly-three types of constraints in mobile multimedia networks which are defined below

4.2.1.1 ADJACENT CHANNEL CONSTRAINT

It is not possible to give the same channel to certain pairs of radio cells at the same time under Adjacent Channel Constraints (ACC). Optimizing channel distribution within a given cell to achieve maximum frequency dispersion within that cell could help reduce ACC.

4.2.1.1 CO-CHANNEL CONSTRAINTS

It is not possible to allocate frequency spectrum to neighboring radio cells in Co-Channels Adjacent at the same time.

4.2.1.2 CO-SITE CONSTRAINT

Two channels can coexist in the same cell if the frequency difference between the channels is small enough.

The problem of channel allocation in mobile multimedia networks has been-addressed with many heuristic algorithms such as Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), Fuzzy Logic (FL) and genetic algorithms (GA).

In mobile multimedia networks, the DCA scheme is introduced in this chapter. The problems of optimal channel allocation have become increasingly important over years, due to the limited frequency range and the increasing demand for multimedia services. But a channel allocation strategy is crucial for making the most of a system's channels as it handles the available channels in each cell.

4.3 MOBILE/CELLULAR NETWORK MODEL

According to Figure 4.1, the geographical model is a collection of parallelogram-shaped cells that are next to one another and do not overlap. These cells are believed to have a hexagonal structure. When a single new call reaches a single cell in the network (the

host cell) at time t, nothing else changes. Channel reuse in cellular systems is both unavoidable and strongly connected to co-channel interference. The degree of co-channel interference decreases as the reuse distance increases. Reuse efficiency drops when number of cells per cluster grows due to a lengthy reuse distance. Therefore, the co-channel interference level and reuse efficiency should be considered while determining frequency reuse pattern. It is possible for two cells to share the same channel simultaneously up to a certain minimum reuse distance, which is the smallest normalized distance that may be tolerated. In all-directions from the host cell, this forms an interference area that extends up to cells. While running on cellular model, the model doesn't take startup into account, but rather the condition at an-intermediate time instant t when network is serving number of calls.

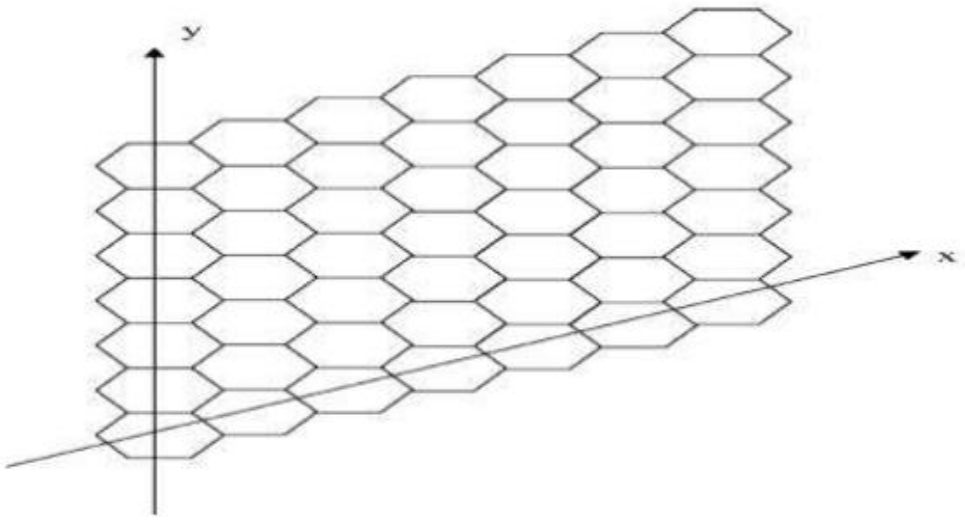


Figure 4. 1 Mobile/ Cellular Network Model

4.3.1 PROBLEM REPRESENTATION

In order to-allocate a channel from a pool with a restricted-number of available channels, the suggested model took the minimal interference channel assignment issue into account.

A total of C channels, each with an identical bandwidth, make up the accessible frequency spectrum and is numbered serially as C = {c1,c2,...cmax} and a system of m cells is represented by M = {m1,m2 mn}.

4.3.1.1 CHANNEL ALLOCATION MATRIX AND VECTOR SOLUTION

Let total cells and channels in networks are denoted by M and C. Then, for this network

framework, a $M \times C$ matrix A, called channel allocation matrix whose (i, j) h components are given-by

$$Aij = \begin{cases} 1 \\ 0 \end{cases} \; if\ channel\ j\ is\ currently\ being\ used\ in\ cell\ i\ otherwise$$

$$\forall\ i = 1,2, \ldots \ldots \ldots, M, j = 1,2,\ldots..\ C$$

Assume M = 4, C = 10 & Channel s 3,4 are right now being-used in cell 1, Channel 6 in cell 2, Channel 1 in cell 3 & Channel 3,7 in cell 4. Now channel allocation-matrix is shown-below table 4.1

Table 4. 1 Channel-Allocation Matrix

		CHANNELS									
		1	2	3	4	5	6	7	8	9	10
CELLS	1	0	0	1	1	0	0	0	0	0	0
	2	0	0	0	0	0	1	0	0	0	0
	3	1	0	0	0	0	0	0	0	0	0
	4	0	0	1	0	0	0	1	0	0	0

Cell k, which is currently handling [traf(k)-1] calls—where traf(k) is the sum-of all incoming and outgoing traffic in cell at time t—is assumed to be location of new call request. The-whole system is free of undecided-calls and calls that are in process.

It may be possible to reassign channels to continuing calls- in cell k, but we need to find a way to make room for the incoming call on an available channel. An appropriate setup would be an X-dimensional vector of channel numbers with a length of traf(k). This vector would represent the set of-channels assigned to-cell k for traf(k) number-of calls at the given time-instant.

If M= 4, C= 10, and a viable solution-is [1 2 7], then V = [1 1 0 0 0 1 0 0 0] would be the {0, 1}-value vector of-length C that stores the information about new channel

assignment in-cell k for every acceptable arrangement. Without a doubt, V is balanced, or one-to-one, function of X.

4.4 HOPFIELD NEURAL NETWORK

In 1982, Dr. John J. Hopfield-developed a kind of artificial-neural network called Hopfield Neural-Network (HNN). These networks may be either recurrent or completely integrated. By making use of an auto-associative memory, HNN stands in for an alternative neural computational paradigm. A paradigm for comprehending human memory is also provided by HNN. Primarily, HNN is trained using simulated neurons. number of inputs to these-artificial neurons is N. A weight wi is connected to each input i. They produce something as well. Until -neuron is updated, output state is preserved. following steps are involved in updating the neuron: weighted-sum of all inputs, $\sum i\ w_i x_i$, is computed after determining the value of -each input, x_i.

I. The total inputs-got from different neurons and threshold function-estimate weight value of each-neuron, denoted by

$$ui = wij\ vj + xi$$

Where vj shows states of neurons.

II. State- of every neuron update naturally- with assistance of neuron threshold rule with threshold-THD as shown by

$$vi = \{ \begin{matrix} 1 \\ 0 \end{matrix} \quad if\ U > TH$$

$$otherwise$$

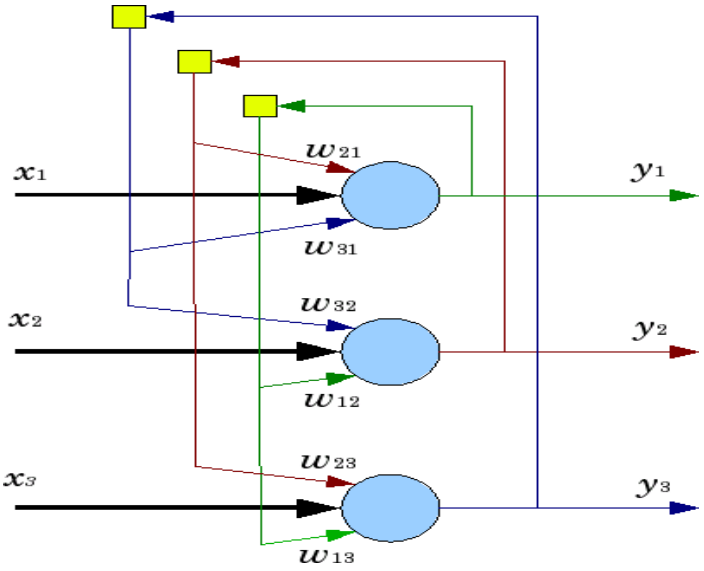


Figure 4. 2 Architecture of Hopfield Neural Network

Output state of neuron is set to +1 if weighted input sum is larger or equal to 0. It is set to -1 if the weighted input-sum is smaller than 0.

A neuron retains its-output state until it is updated again.

$$y = \begin{cases} 1 & \sum w_i x_i \geq 0 \\ -1 & \sum w_i x_i \leq 0 \end{cases}$$

4.4.1 FORMULATION-OF HNN ENERGY FUNCTION

An energy-function formulation E demonstrates how well HNN model performs when it comes to solving the problems associated with dynamic channel-allocation. Several references have addressed the construction of HNN energy function (E).

$$E=\frac{1}{2} x^t W x+b^t x$$

Where

x = Input-vector for channel-assignment;

b = Bias-vector identified by-constraints;

W = Symmetric weight-matrix for HNN.

Channel-allocation issue is formulated and captured using the HNN-model in DCA. The literature-review reveals that several DCA methods have been-discussed in depth, and it demonstrates how an-energy function may stand in for CPA in mobile multimedia networks-when the traffic load is distributed randomly. Channel allocation problems in mobile-network DCA approaches are-handled by new energy function that represents the hard and soft-channel allocation methodology. A fitness or energy function may be expressed in the following way:

$$\boldsymbol{E} = \frac{A}{2}\sum_{j=1}^{C}\sum_{\substack{i=1 \\ i\neq k}}^{M}(V_k, j\,.A_{i,j}.Interf(i,k)) + \frac{B}{2}\left[\sum_{j=1}^{M}(V_{k,j}) - Traf(k)\right]^2$$

$$-\frac{C}{2}\sum_{j=1}^{C}\sum_{\substack{i=1 \\ i\neq k}}^{M}\left(V_{k,j}\,.A_{i,j}\,.\frac{1-Interf(i,k)}{Dist(i,k)}\right)$$

$$-\frac{D}{2}\sum_{j=1}^{M}(V_{k,j}\,.A_{k,j}) + \frac{F}{2}\sum_{j=1}^{C}\sum_{\substack{i=1 \\ i\neq k}}^{M}(V_{k,j}\;.A_{i,j}\,.[1-Res(i,k)])$$

$$+\frac{G}{2}\sum_{j=1}^{C}[Free_j\;.(1-V_{k,j}) - H]$$

Where

M Total cells-used in system.

C Total available-channels in tsystem. H

Total-available handoff-guard

channels.

Ai,j Allocation table elements-denote 1 if channel j is-assigned to cell i, 0, Otherwise.

k number of cells used in call dropping-or arrival.

Traf(k)Available-requested channel at cell k.

Vk, j Assignment of cell of interest.

Dist.(i, k) Adjacent cell-distance between cell i & k.

Interf (i, k) Channel compatibility-matrix set to 1 if assignment of a

Channel in cell i is not-compatible with same channel in cell k, 0, Otherwise.

Res(i, k)-Channel reuse-matrix (its value is 1 if-cells i and k belongs to the same result pattern, 0, otherwise).

In order to solve CPA, which islikely to have a base value that corresponds to good-solution (Xbest) for new channel-allocation in cell k, energy or fitness function mentioned above is used. How energy function works in relation to CAP The following was covered:

$$f_1(A) = \sum_{j=1}^{C} \sum_{\substack{i=1 \\ i \neq i^*}}^{M} V_j . A_{i,j} . Interf(i,k)$$

Where Vj denotes jth component of V & (i, k) is function which-returns 1 if the cells i and k interfere, else-it returns 0. This-term adds 1 for-every cell, interfering-with k, which uses channel employed in k. It subsequently-guarantees that solution with no interference-gives better (smaller) fitness values.

$$f_2(C) = -\sum_{j=1}^{C} \sum_{\substack{i=1 \\ i=k}}^{M} V_j . A_{i,j} \frac{1 - Interf(i,k)}{Dist(i,k)}$$

Where Di (i, k) is standardized-Euclidean distance between the centers of cells i and k. This-deals with packing condition. Hence $Inte$ $(i, k) = 0$ if, $Disti, k \geq RD$.

$$F_3(D) = -\sum_{J=1}^{C} V_j \, A_{kj}$$

In-order to minimize the frequency with which mobile node being serviced changes its Channel, it subtracts 1 anytime channel that was previously in use by cell $i\prod$ before the new call entered acceptable solutions, specifically in the current configuration.

$$f_4(F) = \sum_{j=1}^{C} \sum_{\substack{i=1 \\ i \neq k}}^{M} V_j A_{ij} \{1 - res(i,k)\}$$

Here $r\,(i, k)$ is function which-returns 1 if cells i and k belong to same "reuse-scheme", otherwise it-returns 0.

In our-approach, we have not-considered following parameter-because this term is always equal to-zero

$$\left[\sum_{j=1}^{M} (V_{k,j}) - Traf(k)\right]^2$$

Finally, the energy-function (E) is represented by

$$(E) = W1.\, f1(A) + W2.\, f2(C) + W3.\, f3(D) + W4.\, f4(F)$$

The relevance of various phrases is determined by the weights, which are denoted as $Y1$, $W2$, $W3$, and $W4$. Clearly, $f1(A)$ should take into account the hard interference, which should take precedence over the various elements pertaining to soft interference. Therefore, coefficient values-are $W1 = 7000$, $W2 = 1.2625$, $W3 = 0.01$, $W4 = 4.17625$.

4.5 DESCRIPTION OF-BENCHMARK PROBLEMS

This study takes into-account two types of benchmarks throughout the simulation procedure. According to 21-cell structure, represent the first group of issues. Nevertheless, problems with HEX1 and HEX3 have been ignored by this method. While KUNZ1–KUNZ4 denotes second class of issues, this method-has just taken KUNZ1 & KUNZ2 into account. As a kind of global optimization, we give a number of potential alternatives for allocation. Research on HNN-based channel allocation on HEX 1 & KUNZ 1 has been conducted to enhance channel allocation even more.

The network cell count (M), channel count (C), and demand-vector (D) are variables used to represent each issue. The ibh component of demand vector shows traffic

demand in-cell i, where i = 1, 2, M. In Table 4.2, each issue is detailed.

Table 4. 2 Benchmark Problems

Problem	Cells - (M)	Channels -(C)	Demand-Vector (D)
HEX 1,	21	37	2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2
HEX 3,	21	21	1,1,1,2,3,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6
KUNZ 1,	10	30	10,11,9,5,9,4,5,7,4,8
KUNZ 2,	15	44	10,11,9,5,9,4,5,7,4,8,8,9,10,7,7

We made various modifications, as-given in table 4.3, to make-each issue more favorable using this approach. To-determine the configuration of mobile networks, we assume that all-cells are arranged in parallelogram. Therefore, for every set of problems, we express the number of-cells & channels as r × c, where r & c are-whole integers. We try to choose r & c in way that keeps rows and column- balanced to the best of our abilities while keeping r × c.

Table 4. 3 Modification on Benchmark Problems

Problems	R	C	Cell k	Number of calls in service in cells-at time t as given in Demand Vector
HEX 1,	3	7	Random	2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2
HEX 3,	3	7	Random	1,1,1,2,2,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6
KUNZ 1,	2	5	Random	10,11,9,5,9,4,5,7,4,8
KUNZ 2,	3	5	Random	10,11,9,5,9,4,4,7,4,8,8,9,10,7,7

A cell's primary responsibility is-to assign channel to each incoming call. Now, choose any cell k and before call request reaches k at time t, there are $\boldsymbol{Pi}$ calls happening in the i^{th} cell for i=1,2. M, $i \neq k$ and (Dk -1) calls in the kth cell, where Dk represents the k^{th} element of demand vector D, k=1,2.....M. In-order to circumvent CCC, which displays status of progressing calls in each cell prior to the arrival of new calls and so establishes an initial condition, we have built a M ×C channel-allocation matrix-for each issue based on previous discussion. allocation matrix for the benchmark-issues was constructed using HNN, as-shown in Tables 4.4, 4.5, 4.6, and

4.7. The rows reflect the number of cells & the columns represent the number-of channels.

Table 4. 4 Channel Allocation-Matrix for HEX 1

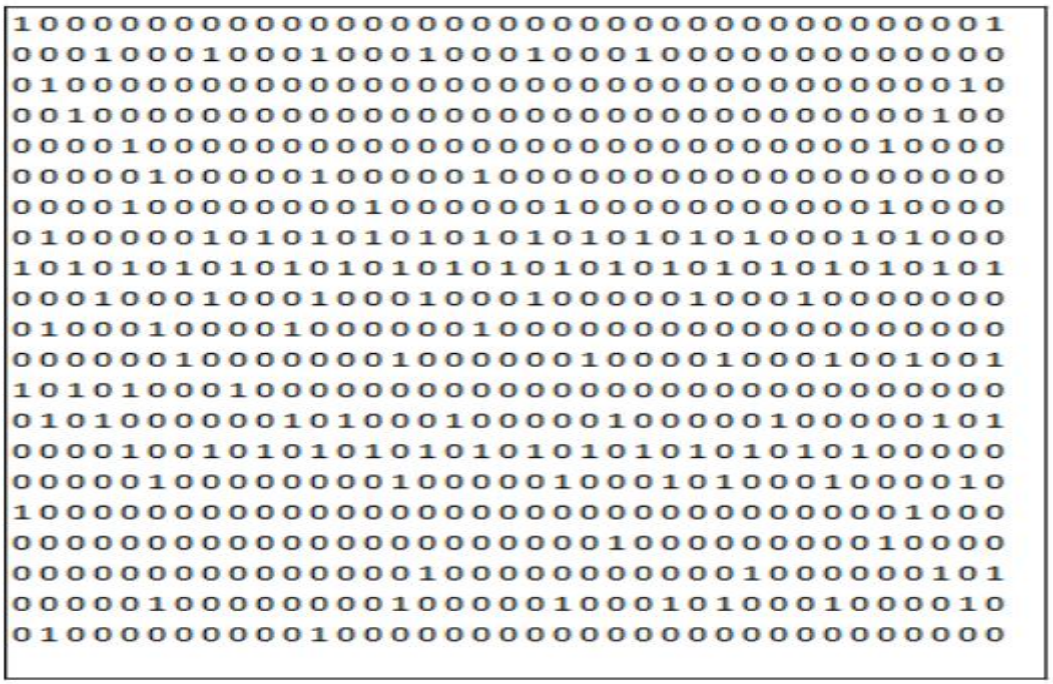


Table 4. 5 Channel-Allocation Matrix for HEX 3

1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
1	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	1	0
0	1	0	0	0	1	0	1	0	0	0	1	0	0	1	0	1	0	0	1	0
0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	1	0	0	1
1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0
0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	1	0
0	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0
1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	1
0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0
0	1	0	1	0	0	0	0	0	1	0	0	1	0	1	0	0	0	1	0	1
0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0
1	0	0	0	0	1	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0
0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	1	0
0	1	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1

Table 4. 6 Allocation-Matrix for KUNZ 1

1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1
0	0	0	0	1	0	1	0	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0
0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
1	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0

Table 4. 7 Channel Allocation-Matrix for KUNZ 2

1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

4.6 RESULTS & ANALYSIS

In the examples given above, such as HEX 1, HEX 3, KUNZ 1, & KUNZ 2, channel allocation-model based on HNN is used. I assumed that for every-simulation of a certain issue, we would expect an incoming call-request in same cell when networks had a comparable assignment matrix, thus we ran-at least 500 simulations under similar beginning conditions. After 500 rounds of the HNN, the outcomes of each simulation are different. All of the outcomes are generated via the use of MATLAB and a C program to minimize the fitness function (E) through the use of HNN. When updating energy functions, if any part of the position or-speed goes above maximum allowable values or falls below minimum allowable values, it is-set to the corresponding maximum or minimum, respectively. But-only integer-values (Channel numbers) are allowed in the end product, which is vector of real-numbers between 1 and C.

For the simulation following-assumptions have been-considered

I. Co-Channel-distance is 2

II. Adjacent-Channel distance-is 3

III. The number of incoming- calls lays in range of 0 t0 250 & change dynamically.

IV. Initial population size-was taken 50.

V. Distance between two base-stations is 2 Km. remains-unchanged.

For HEX1 for - channel allocation - where demand vector

D = [2,6,2,2,2,3,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2], It proves that in the early stage, there are three-active calls in-cell 6 (k = 6). A new channel has to be allocated if new call arrives in cell at same time. We were able to allocate channels with the least amount of interference by using our model. call is refused after-each simulation if simulation result does not-comply with CCC. The Cell-based Call Rejection-Probability (CRP) is defined as follows so that we may judge how-well our method works:

$$\text{CCRP} = \frac{\text{Number of times new incoming-call is blocked in host cell Total}}{\text{number of new calls-request made in host cell}}$$

It should be emphasized that this-parameter CCRP differs from call-blocking probability used in , which describes cellular network overall, and instead describes specific cell under a specified beginning situation. You can see the CCRP calculations for all the resolved concerns in-Table 4.8.

Table 4. 8 Cell-Based-Call Rejection

Problems	**Host-cell *k***	**Number of - Simulation**	**Number of times call is Rejected**
HEX 1,	6	104	21
HEX 3,	5	105	32
KUNZ 1,	7	110	39
KUNZ 2,	7	100	20

CCRP for cell in HEX 1: We have determined CCRP for-channel assignment in specific-cell *k* of HEX 1. As shown-in Fig. 4.3, CCRP in a specific cell-decreases as number of iteration increases.

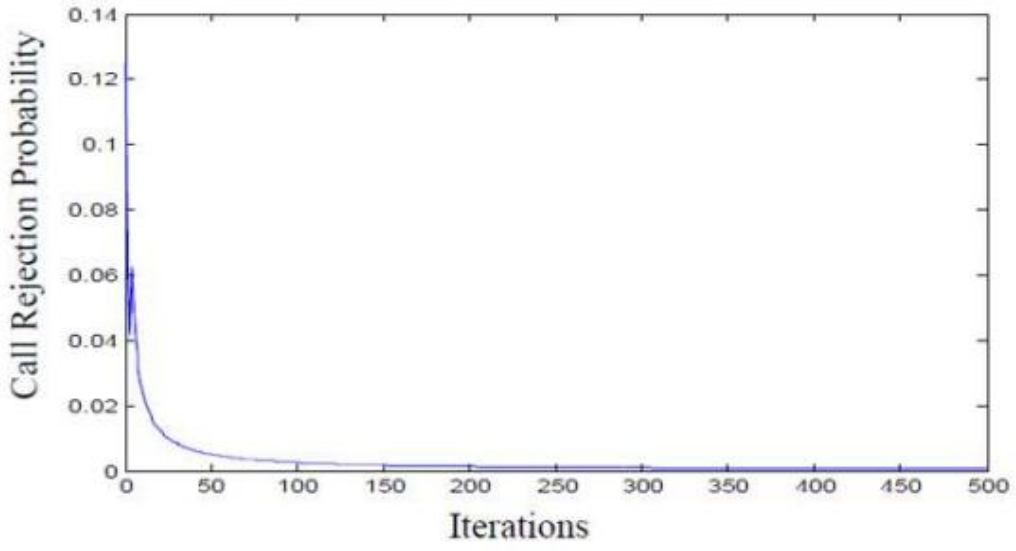


Figure 4. 3 Call Rejection-Probability for HEX1

In table 4.9, we can see the comparison between the convergence ratios achieved by HNN and GA on-HEX1, HEX3, KUNZ1, and KUNZ2.

Table 4. 9 Comparative-Analysis of Convergence Ratio

No. of Iterations	Convergence Ratio-using HNN				Convergence-Ratio using GA			
	HEX 1	HEX 3	KUNZ1	KUNZ 2	HEX 1	HEX 3	KUNZ 1	KUNZ 2
200	85%	83%	80%	82%	61%	58%	58%	62%
300	95%	94%	89%	92%	92%	93%	90%	94%
400	100%,	99%	93%	98%	95%	94%	93%	95%
500	100%,	100%	95%	98%	95%	95%	97%	96%

One way to evaluate model's-efficacy is by looking at its call-rejection ratio. During the 500-cycle examination of call-blocking ratio variation, all benchmark difficulties are taken into account. Figure 4.4 shows the outcome that was achieved.

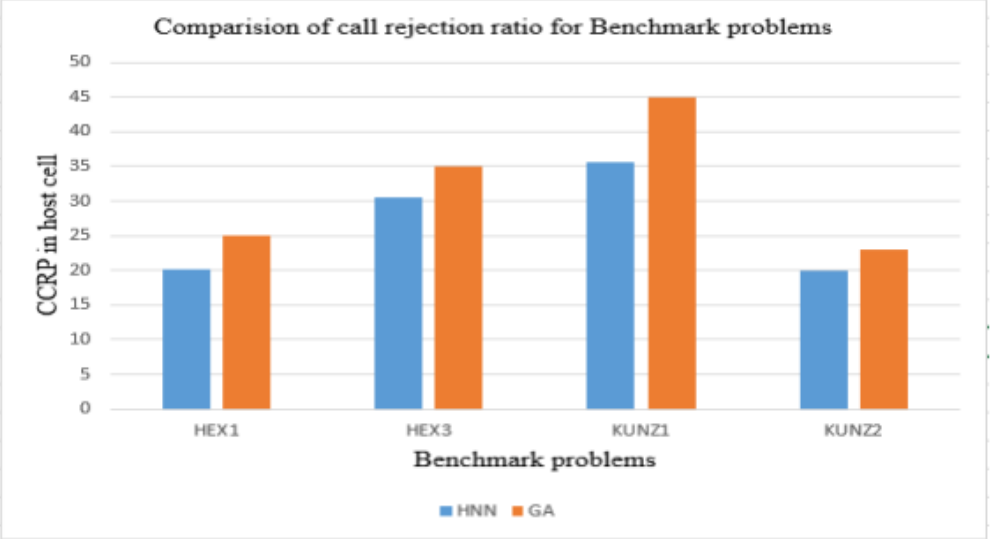


Figure 4. 4 Call Rejection-Ratio for Benchmark Problems

The findings show that the call rejection-probability is much lower than permissible blocking probability for every case. The improved and optimized channel assignment

has allowed for higher bandwidth consumption, which in turn has met the needs of-users and their-applications.

In order to make the most of the channels in mobile-multimedia networks, this chapter introduces a dynamic channel-allocation model that is based on HNN. In-order to assess the channel-allocation issue, an HNN-model has been created. There been four benchmark issues that model has been tested on. Following extensive testing of the model with different-population sizes, we have determined that 100 is the sweet spot for optimal response. As the iteration count grew, the Cell-Based Call-Rejection Probability (CCRP) fell. The technique converges with a minimal number of iterations, which is quicker than other algorithms like Genetic technique (GA). This saves time and increases the usage of wireless system's channels.

CHAPTER 5
NEURAL FUZZY-BASED CALL-ADMISSION CONTROL FOR ENHANCED QOS IN HIGH-SPEED MOBILE MU-TIMEDIA NETWORKS

5.1 BACKGROUND

A multitude of multimedia apps and services rely on fast mobile multimedia networks to keep up with the ever-increasing demand from mobile consumers. When it comes to handling bursty-traffic & ensuring various-Quality-of-Services (QoS) like cell loss ratio, resource utilization, less blocking-probability & dropping-probability, user mobility, and more, high-speed networks rely on mobile/wireless communication networks. These networks provide wireless communication with both static & dynamic hosts. Efficient-channel assignment and CAC systems are crucial in multimedia high-speed network-environments for improving resource management and ensuring end users get an adequate level of quality of service.

For real-time multimedia network applications, the quickest network technologies, such as 4G & 5G networks, can provide-data transfer rates of up to-450 Mbps while maintaining efficient service quality. In-order to develop effective policies that maintain smooth handoffs across heterogeneous-networks and meet QoS requirements, users of advanced mobile multimedia devices are always seeking the optimal connection, regardless of where they are or what time of day it is. This makes it very challenging to choose the optimal network for taking new calls without lowering the quality of service for existing calls. Problems with decision-making accuracy and uncertainty plague high-speed networks (4G) as a result of factors such as the ever-increasing number of mobile access points, fluctuating channel propagations, unpredictable user mobility, and unexpected changes in network load.

Many researches have been conducted in the area of mobile-multimedia networks, and it has been proved that fuzzy-logic (FL) and artificial-neural networks (ANN) based models are more suitable to solve the CAC problem.Neuro-Fuzzy model has-been widely applied to improve the performance of-existing CAC policy in high-speed mobile multimedia networks. According to results of previous studies, neural fuzzy controller is capable of controlling complicated problems of system. In this context, FL is able to cope with imprecision in the real world, & the input-network traffic & system-capabilities are defined by self-learning ability of the classic NN model, Self-Organization-Map (SOM). The NN provides a stable dataset that can be used for

training, which improves FL's capabilities. By doing so, the fuzzy system may be fine-tuned until it is a perfect fit with training data. In mobile-multimedia networks that employ a neural-fuzzy method, each-cell is considered as an-autonomous controller, having a different behavior model, which depends on user's mobility and the geographical properties of cell. Even though the available bandwidth varies with the call state, it is important to-have proper quality-of service standards, to minimise the likelihood of new-calls being blocked and handovers-being lost. Fuzzy-set theory provides powerful computational-model to handle-errors in real world. Fuzzy techniques are able to-adapt to changing, inaccurate, & realistic situations, showcasing their flexible performance.

The authors of created smart-system that can handle incoming-traffic in varied mobile network-environment by proposing fuzzy-neural-based CAC approach that combines the learning-function of recurrent-neural radial basis function with fuzzy logic control function. A fuzzy-based CAC technique has been-suggested to system-performance utilizing shadow cluster idea & to maintain QoS-level of current calls. We have compared performance of type-2 fuzzy-logic controllers-with type-1 fuzzy-logic controllers and designed an integrated-fuzzy logic-based CAC-for 4G networks to improve quality of service provided with Karnik-Mendel & Wu-Mendel models.

In-order to enhance quality of service for-continuous service-availability in high-speed mobile-multimedia networks, this chapter-presents Neural Fuzzy-based Call Admission-Control (NFCAC) model that covers the largest geographical region. NFCAC controller architecture is hybrid learning-method that combines Self-Organizing Map Neural-Networks and Fuzzy Logic. This strategy makes use of a two-stage learning procedure. The first stage is to create rules and set the initial-membership functions by a self-organized learning technique. membership functions-are then optimally adjusted in Phase 2, using a supervised-learning algorithm, to achieve desired results. simulation results NFCAC model enhanced utilization of the system and reduced the CBP and CDP with less training time. results of proposed approach are compared to the results of existing CAC methods-based on FL & NN to verify functionality-of proposed approach.

5.2 FUZZY LOGIC

Originally proposed by Lofti A. Zadeh, Fuzzy-Logic (FL) stands for vague and ambiguous information. Use it to deal with-complicated issues when the variety of

possible solutions is more useful than simple yes or no. Fuzzy membership-functions, which may take on values between 0 and 1, are-used to describe items that make up a fuzzy set. Nonlinear system performance has been the primary focus of fuzzy logic's application. A collection of fuzzyr-ules may effectively capture and describe nonlinear systems. Fuzzy-logic (FL) is rule-based architecture that relies on-four main components: DE fuzzy, fuzzy rule-base, inference-engine, and fuzzy. In this-case, a fuzzy set F has been-defined in discourse world U by defining language variable x in U by $(x) = \{T\ x^{1}, T^{2}\ x, T^{3}\ x \ldots\ldots\ldots\ldots T^{k}\}$ and $(x) = \{M^{1}\ x,\ M^{2}\ x,\ M^{3}\ x,\ Mk\ x\}$, where

(x), the fuzzy input is set of x and (x), set of rules that are connected-with each-input with their meaning. According-to fig. 1, fuzzifier convert an input x of fuzzy-set T^{k}x with degree of membership-function M^{k}xi = 1 … … … …. m.. A series of linguistic assertions that-establish fuzzy logic-based relationship between m-dimensional inputs xi & n-dimensional outputs y is stored in fuzzy rule base, which also contains domain control-information that defines the fuzzy IF-THEN rule. After the fuzzification is finished, inference engine creates decision parameter that uses the input language variable-values of T(xi) to derive output language variable-values of-T (yi), which are fuzzy IF-THEN-rules. When DE fuzzifier has access to the T output linguistic-variable yi, it uses defuzzification-function to produce decision-making non-fuzzy values from yi. Previously established-schemes' domain information is housed in fuzzy logic controller.

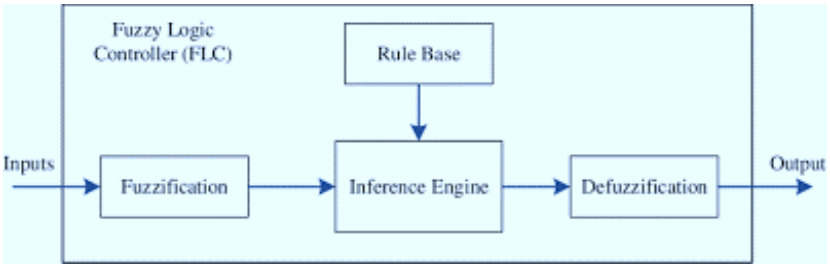


Figure 5. 1 Basic structure of a fuzzy logic-controller

5.3 NEURAL- FUZZY CALL ADMISSION-CONTROLLER

Suggested model's neural-fuzzy call-admission controller is based on a five-layer neural fuzzy network-architecture. NFCAC controller has five-layer design, as seen in figure 5.3. Linguistic inputs are-processed by-nodes in layer 1, and two-linguistic outputs are generated by nodes-in layer 5. Two outputs are used by network: one for delivering tanning data & producing the intended result, and second-for carrying the decision signal, which is used to make actual output. Also, the words nodes in layers 2 and 4 serve as membership function for corresponding language variables. In layer 3, every node stands for fuzzy rule, and they all work together to provide afoundation for fuzzy inference rules. connections between layers 3 and

4 are what drive the inference process. In layer 3, the connections provide the requirements, and in layer 4, they define outcome of rule nodes, respectively. whole relationship between input language nodes & its parallel-term nodes is represented-by the linkages between-Layer 2 & Layer 5.

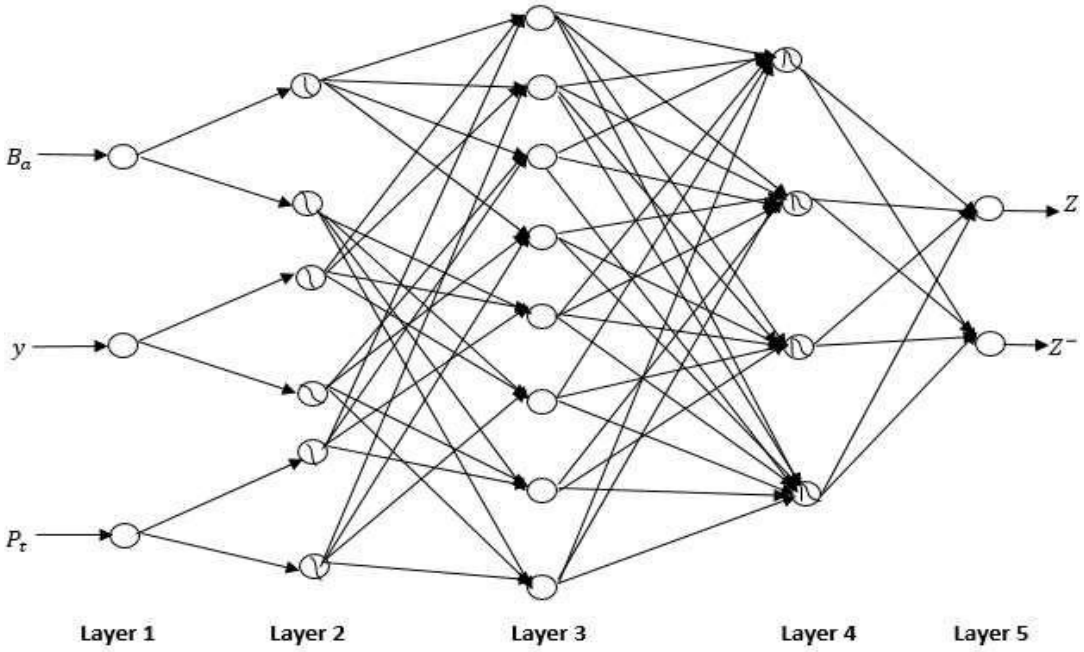


Figure 5. 2 NFCAC Controller Architecture

There are three inputs to NFCAC controller: the available bandwidth (Ba), an indication of network traffic-congestion (y), cell loss ratio (Pt), and an output decision signal (Z) that indicates whether new call request is accepted or-rejected. Widely used in CAC rules based on fair-bandwidth allocation, equation (1) represents

the available bandwidth.

$$Ba = Bt(Total\ Bandwidth) - Bu(Used\ Bandwidth)$$

You may get an accurate picture of network's system and the current degree of traffic congestion with help of the network-traffic jam indicator y. The feedback- based system's capacity to self-modify & provide powerful & secure operation is represented by cell loss ratio Pt.

With the NFCAC system, fuzzy inference-process is linked to each layer. NFCAC controller uses an-activation function for output & network input function denoted as (k)(u(k)).

$fn_i^{(k)}$ ($u_i^{(k)}$) for all -nodes i to k, where $u$if(k) represent possible set-of input to node i
in layer k form node j in layer($k-1$). details of five layers-are given below.

Layer1. (Input Layer): Every neuron in this-layer is able to interact with the subsequent layer's sharp signals. Where x is number of linguistic-input variables and k is number of current layers, generalized-form of Tk for input-variables is
Ba, y, and $\boldsymbol{U}b$. $\boldsymbol{N}a$, y, and Pb are defined-as follows in NFCAC

$$fn_i^{(1)}(u_{ij}^{(1)}) = u_{ij}^{(1)} \quad \text{and } a_i^{(1)} = fn_i^{(1)}$$

Where $u_{11}^{(1)} = B_a$, $u_{22}^{(1)} = y$, $u_{33}^{(1)} = P_t$, and $1 \leq i \leq 3$ and $1 \leq k \leq 5$.

Layer 2. (Fuzzification-Layer): This layer's nodes get crisp inputs via a fuzzifier. available bandwidth is-defined by the term (Ba) = {Low (L), Medium- (M), High (H)}, and the term for network traffic load adjustment-parameter is T (y) = {High -(H), Medium -(M), Low (L)}. This parameter shows the system's network congestion state, which-can be high, medium, or low; high indicates networks that are completely congested, and low indicates-networks that are free of congestion. One of most crucial parameters for-quality of service, cell loss ratio is-defined as T (Pb) = {High -(H), Medium (M), Low (H)}. There are-six nodes in this-layer for the aforementioned collection of words. In layer 2, every node activated membership-neurons with a bell-

shaped activation function, which defines fuzzy set of neuron. Here is the definition of activation function:

$$fn_i^{(2)}(u_{ij}^{(2)}) = -\frac{(u_{ij}^{(2)} - m_{jn}^{(I)})^2}{\sigma_{jn}^{(I)^2}}$$

$$a_i^{(2)} = e^{fn_i^{(2)}}$$

Where $u_{ij}^{(2)} = a_j^{(1)}$, $1 \le i \le 6$, $j = \lceil \frac{i+1}{2} \rceil$ and $m_{jn}^{(I)}$ and $\sigma_{jn}^{(I)}$ are define mean (or center)

and standard-deviation (or width) for every nth-term of crisp input set from-node j in input layer. If the i^{th} node is-odd then set n=1, otherwise-set n=2.

Layer 3. (Rule-base Layer): Here, one fuzzy rule is associated-with every neuron. Neurons that reflect required matching-conditions of fuzzy control rules—the fuzzification neurons—input data to connections between fuzzy rule-neurons. fuzzy set with-dimensions $(Ba)\times$ T $(y)\times$T $(Pt)\times T(x)$ may be used to describe the fuzzy rule base, according to fuzzy set theory. The dimensions of this set indicate number of inputs in (x). This layer has eight nodes that are-rules. To implement each rule-node in a neural-fuzzy, system, one may use fuzzy AND operation, which is described as follows:

$$fn_i^{(3)}\left(u_{ij}{}^{(3)}\right) = \min(u_{ij}{}^{(3)}; \forall j \in P_i)$$

$$a_i{}^{(3)} = fn_i^{(3)}$$

Where $uij^{(3)} = \quad aj^{(2)}$ and Pi = {j | all jth preconditioned nodes of ith rule}, $1 \leq i \leq 8$.

Layer 4. (Output membership-Layer): Fuzzy sets, which are end product of-fuzzy rules, stand in for neurons at this-layer. Fuzzy union procedures-are used to merge all inputs of output membership neurons. Probabilistic OR-procedures may accomplish this task. There are-two modes of operation in this layer: down-up and up-down. Using the down-up, we may find out if output matches the input's fuzzy inference rules. A-soft admission decision set may be described as $(z-)$= {"Reject" (R), "Weak Reject" (WR), "Weak Accept" (WA), "Accept" (A)}, based on output set (up-down) of linguistic variables.Hence, the acceptance/rejection-decision border of Call may have been specified by NFCAC controller. Four nodes make-up this layer. Fuzzy OR operations are implemented at-each node to incorporate firing strength of fuzzy rules. Hence, we establish

$$fn_i{}^{(4)}(u_{ij}{}^{(4)}) = \max(u_{ij}{}^{(4)}; \forall j \in C_i$$

$$a_i{}^{(4)} = fn_i{}^{(4)}$$

Where (4) = (3) and Ci= {j | all j that have same results of the ith node in the input term set of $z-$}, $1 \leq i \leq 4$.

As part of the system's training-process, the up-down operating-mode is fed output data set. comparable to their purpose in layer 2, nodes in this layer and linkages in layer-5 perform-comparable tasks. bell-shaped fuzzy function, which is-defined as

$$fn_i^{(4)}\left(u_{ij}^{(4)}\right) = -\frac{(u_{ij}^{(4)} - m_j^{(O)})^2}{\sigma_j^{(O)^2}}$$

$$a_i^{(4)} = e^{fn_i{}^{(4)}}$$

Where uij (4) =aj (5), received by up-down operating mode in layer 5, and mj$^{(O)}$ and σj$^{(O)}$ are define mean (or center) and standard-deviation (or width) for-every jth term of $z-$, respectively, $1 \leq i \leq 4$, $j = 1$.

Layer-5. (Defuzzification Layer): In this layer, each neuron-represents single output of neural-fuzzy system.

Here, down-up operation is carried out by first node, while the up-down operation is performed by the second. output fuzzy set is then obtained from these-two nodes. In order-to accept or reject call, first node does down-up operations on decision parameter z−. Lines connecting nodes function-similarly to DE fuzzifiers. Here is function that calculates the defuzzification process:

$$fn_i^{(5)}\left(u_{ij}{}^{(5)}\right) = \sum_{j=1}^{4} m_j^{(O)}\, \sigma_j^{(O)} u_{ij}{}^{(5)}$$

$$a_i{}^{(5)} = U\left(\frac{fn_i^{(5)}}{\sum_{j=1}^{4} \sigma_j^{(O)} u_{ij}^{(5)}} - z_a\right)$$

Where $uij^{(5)} = aj^{(4)}, i = 1, za$ is a decision threshold &

$$U(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise. \end{cases}$$

The code mentioned above demonstrates that new call will be approved if $z^{-} = a1^{(5)}$ and $z^{-} = 1$. During system training, second node is responsible for up-down processing. To ensure the weights are updated properly, it feeds the NFCAC controller the signal it wants. Given this category of nodes, we established

$$fn_i^{(5)}\left(u_{ij}{}^{(5)}\right) = fn_i^{(5)}\left(u_{ii}{}^{(5)}\right) \text{ and } \quad a_i{}^{(5)} = fn_i^{(5)}$$

Where $i = j = 1\ and\ {}_{11}^{(5)} = z.$

5.3.1 SELF-ORGANIZING MAP

When it comes to ANN models for dimensionality reduction, one subset stands out: Korhonen's Self-organizing Maps (SOMs). Combining "self-Organizing" (i.e., learning without supervision via unsupervised competitive learning) with "Maps," which try to adjust their weights to fit the incoming data, is what the term "Self- Organizing Maps" alludes to. In the support vector machine (SOM), nodes stand in for the input patterns so the model can learn them. "Featured Maps" is another name for SOM, as in Self-Organizing-Feature Maps. The primary goal of SOM in this case is to preserve original topological-relations while transferring an entering linguistic-input pattern with m-dimensional-values to less dimensional output-mapped values. The network's output neurons compete with-one another to be triggered and produce neurons. At any given moment, just a single neuron from each group is chosen. A

winner-takes-all neuron is one in which the output neuron is used to-determine the victor of a contest or battle.

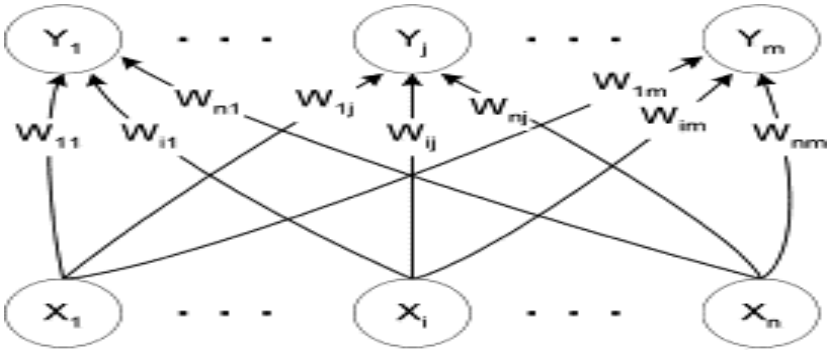


Figure 5. 3 Korhonen's Self-organizing Map Architecture

The author explains how 4G mobile networks employ self-organization maps (SOMs) to increase system flexibility. By substituting highly decentralized regulated resource assignment in 4G mobile network for the centralized one, the author was able to analyze and change the SOM working model using the entropy-based complexity matrix. During mobile network operations, the authors of made excellent use of Korhonen's self-organizing-map to allocate channels efficiently. first part of this method involves a Manhattan-like network pinpointing the user's precise position, and the second part is when SOM decides how to distribute the available resources. By imposing certain constraints on the channel assignment process for both incoming and outgoing calls, this enhances service quality and mobile network performance.

Algorithm of Korhonen's Feature-Maps

[Obtain mean (mi) value by using SOM-algorithm]

Step 1: Set random-values of mi for all NFCAC membership-function (1

$\leq i \leq M$) & value of mi should be lies between as given-below

$$\min_{1 \leq j \leq N} x_j \leq m_i \leq \max_{1 \leq j \leq N} x_j$$

Where M represent membership function for each linguistic input-variables xi and N represents training data set for its corresponding-input variable xj.

Step 2: Set initial learning rate η ($0 < \eta < 1$) and set $j = 1$

Step 3: Calculate the distance di (Winning Neurons) by applying tanning data set xj

$di = |xj - mi|$, $1 \leq i \leq M$.

Step 4: In this step from all available membership function determine

k^{th} Membership function which has minimum distance dk (i.e., dk = min $1 \leq i \leq M$ di). Now-update Mk by

$$Mk = Mk + \eta(xj - mk).$$

Step 5: Check if $j < N$, then-set $j = j + 1$ and GOTO Step 3

Otherwise, Decrease η & GOTO Step 2.

Step 6: Repeat above procedure until $\eta \leq 0$.

For each input & output parameter, winner-take-all circuit finds the smallest value di in step 4. NFCAC controller moves on to supervised learning after self- organized training-phase is complete. A learning procedure called Error Back- Propagation (EBP) is used-to reduce the error **f** for training data-set in order to supervise learning. In order to determine $\sigma E/\sigma w$ for every hidden-layer node used in layers 4 and 2, a feedback channel is implemented starting at output node. The hidden nodes' weight adjustment w is based on following typical learning rules.

$$w^{new} = w^{old} + \eta \frac{\partial E}{\partial w}$$

Layer 2 & layer 4 use the fluctuation of η values to provide high-quality learning rate for the input & output variables defined. η is the learning rate in this context. When updating membership function for specific input variables is unnecessary,value of ϵ will be 0.

Construction of-Training Data Set

A fuzzy bandwidth-estimator is necessary for the training set of new NFCAC call; this estimator is used to determine needed bandwidth. Estimating total available bandwidth is done by Be, network resource estimator. traffic jam indicator y is generated by fuzzy congestion controller, and cell loss ratio Pt is measured by the system-information statistics; CAC function is handled by this controller. Based on-decision signal Z, which is supplied by the NFCAC controller, following is defined-as acceptance or-rejection of new call requests:

If P_t < QoS Then

Accept the new call-request and set Z=1.

Else

Reject new call request and set Z=0.

We keep running the simulation for a certain amount of time without getting any-new call requests in network to validate acceptance decision of a new call. We get numerical data about cell loss ratio from the simulation result P' If $P^f t'$> QoS, the new call is rejected, then-Set Z=0.

Training data is saved in Ba,y, Pt, & Z to be utilized as-inputs (Ba,y, Pt) and output (Z) that is wanted. Through use of fuzzy partitioned-parameters and self- organized training, the fuzzy membership function & fuzzy control rules may be derived. It is possible to generate many workable sets of control rules with just small adjustments to the fuzzy rules by using the first training set to build the first set of rules. Our model chooses a control rule set for training-data from all the feasible sets; set that produces the smallest square error E is defined-as follows.

$$E = \frac{1}{2}\sum_{i=1}^{N}[z(t_i) - z^{-}(t_i)]^2$$

The above-equation state that after applying the 500 number of-tanning data set at time ti the desired-output $z(ti)$ and actual output $z{-}(ti)$ are obtained.

In the absence of a training set, the N-nearest neighbor approach and Korhonen's SOM feature-maps methodology are used to-estimate the starting point of membership functions. For set of input tanning data xi for x, membership function is estimated for each i^{th} linguistic variable mi if the estimated starting position of the NFCAC membership functions follows the algorithm's description.

5.4 RESULTS OF SIMULATION

NFCAC model is designed to be simulated on very high-speed wireless multimedia network, such as LTE/4G. whole simulation was carried out using MATLAB R2017. In the simulation, the following parameters are defined: the number of cells is 100, the mean channel holding time is 120 (1/μ), and the arrival of new calls follows the poison process.

Type-1, or real-time, input-traffic is responsible for handling incoming and outgoing voice calls, whereas type-2, or non-real-time, is responsible for handling data calls. The NFCAC controller's rule construction & input variables are first created and changed using NN learning method based on previous knowledge about CAC schemes. Figures 5.4 & 5.5 demonstrate fuzzy membership functions of type-1 & type-2 traffic, respectively, for given set of input variables. available bandwidth is reduced by deducting bandwidth used by both new and current calls. network system will allocate Bb of its total bandwidth to traffic class-1 and remaining (Bt-Bu) bandwidth to traffic class-2 if the system's capacity is Bt. using the channel borrowing technique, the system allots more bandwidth to the necessary traffic class, ensuring that the network (bandwidth) is used properly. In this way, the average value of the initial membership function of accessible bandwidth (I) a is set (i.e., $m^{(I)}$ is set for-Low (L), $m^{(I)}$ is set for Medium (M) & $m^{(I)}$ is set-for High (H)).

11 12 13

In addition, the three wireless network states—congested full (H), partly congestion (M), and congestion-free (L)—could be-used to evaluate network traffic jam indicator's performance during the NFCAC model's simulation. Hence, the data collected may be used-to enhance initial membership-function of y. mean value $_{jn}^{(I)}$is set for congestion full (H), partially-congestion (M) and congestion-free (L) states of wireless networks (i.e., $m^{(I)}$for (H), (I) for (M) & $m^{(I)}$for (L)). In order to determine average value of membership function, which is (I) when QoS criteria are not fulfilled (H), main-membership function of cell loss ratio is determined using specified QoS parameters, $m^{(I)}$is set when the QoS requirements are partially satisfied (M), & $m^{(I)}$is determined after user's needs (L) and quality of service (QoS) are met. Presently, beginning value of the-output term set ($z-$) for mean value is determined by fuzzy membership-function $m_j^{(O)}$ is set. value of $m_j^{(O)}$ is set-between the range of 0 and 1. NFCAC model enters supervise learning-phase after first simulation phase yields-an ideal collection of fuzzy rule-structures (as illustrated in Table 5.1).

Table 5. 1 The Fuzzy IF-THEN Rules Composed By the FIS

Rule number	Description of IF-THEN rules
1	If Ba is L, y is H, & Pt is H, $z-$ is R.
2	If Ba is L, y is H, & Pt is M, $z-$ is R.
3	If Ba is L, y is H, & Pt is L, $z-$ is WR.
4	If Ba is L, y is M, & Pt is H, $z-$ is R.
5	If Ba is L, y is M, & Pt is M, $z-$ is R.
6	If Ba is L, y is M, & Pt is L, $z-$ is WA.
7	If Ba is L, y is L, & Pt is H, $z-$ is WA.
8	If Ba is L, y is L, & Pt is M, $z-$ is A.
9	If Ba is L, y is L, & Pt is L, $z-$ is A.
10	If Ba is M, y is H, & Pt is H, $z-$ is WR.
11	If Ba is M, y is H, & Pt is M, $z-$ is WA.
12	If Ba is M, y is H, & Pt is L, $z-$ is A.
13	If Ba is M, y is M, & Pt is H, $z-$ is WA.
14	If Ba is M, y is M, & Pt is H, $z-$ is A.
15	If Ba is M, y is M, & Pt is L, $z-$ is A.
16	If Ba is M, y is L, & Pt is H, $z-$ is A.
17	If Ba is M, y is L, & Pt is M, $z-$ is WA.
18	If Ba is M, y is L, & Pt is L, $z-$ is A.
19	If Ba is H, y is H, & Pt is H, $z-$ is WA.
20	If Ba is H, y is H, & Pt is M, $z-$ is A.
21	If Ba is H, y is H, and Pt is L, then $z-$ is A.

22	If Ba is H, y is M, & Pt is H, $z-$ is WA.
23	If Ba is H, y is M, & Pt is M, $z-$ is A.
24	If Ba is H, y is M, & Pt is L, $z-$ is A.
25	If Ba is H, y is L, & Pt is H, $z-$ is A.
26	If Ba is H, y is L, & Pt is M, $z-$ is A.
27	If Ba is H, y is L, & Pt is L, $z-$ is A.

Figures 5.4 & 5.5 show the calculated membership-function of input language variables for type-1 (voice) & type-2 (data) traffic, respectively.initial fuzzy membership functions of Ba and $z-$, which were established heuristically, must be optimized during the supervise learning-phase. Membership-functions, seen in figure 5.4, are specified as follows for class-1 type traffic for membership function of Ba, mean value $m^{(I)}$, $m^{(I)}$and $m^{(I)}$of membership function, L, M, & H are assigned. training period in the supervise-learning phase is reduced since a dramatic modification has been-made to membership function of Ba as we get membership function of y.

Here set of three values of η {= 0, y = 0.001, Ba, $z-$ = 0.01} is the variables Pt, y, Ba, and $z-$ are defined in that order. Since η is equal to zero for kb, the membership function of kb will not change. Our next step is to have a look at the average values and membership functions of output variable $z-$.

$m_1^{(O)}$ and $m_3^{(O)}$ of membership function R and WA are slightly-increases from 0 to 0.05 &from 0.60 to 0.67, respectively.

According to average values of R and WA, the impacts of rejection & weak acceptance have been marginally amplified. set of four terms that make up output variable $z-$ may be rearranged to focus greater emphasis on one of three-variables that remain unaltered. Because the other three variables will have their usefulness reduced, position can only be changed within a restricted range due to this modification.

NFCAC-controller may now recover some spare bandwidth in system to accept new and handoff-calls more effectively, all while maintaining the QoS criteria, thanks to the modification in membership function of $z-$. Figure 5.5 shows the findings for class-2 traffic, which may be obtained by using the same phenomena.

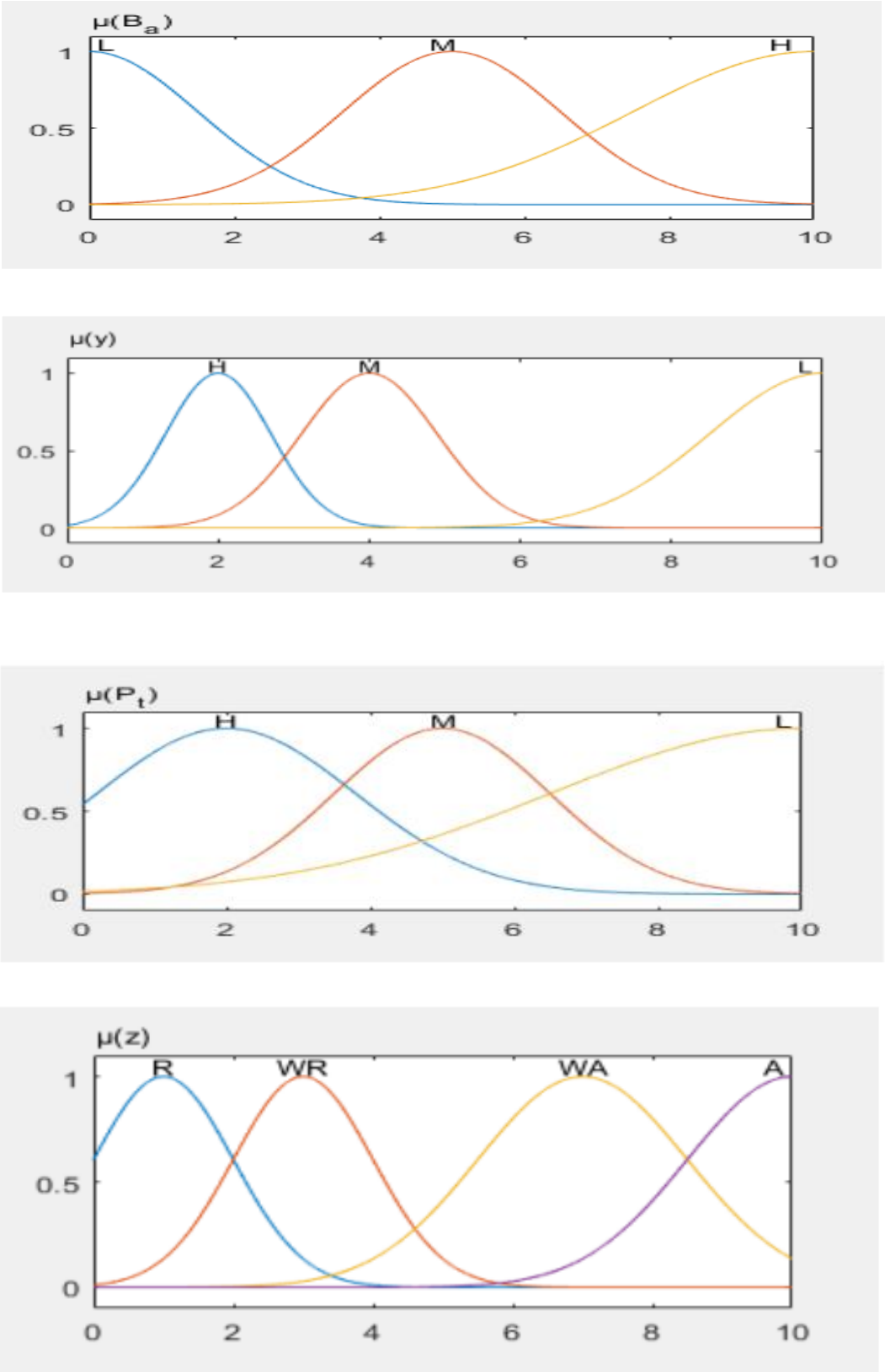


Figure 5. 4 Membership-Function Of Ba,y Pt and z For-Type-1(Voice)

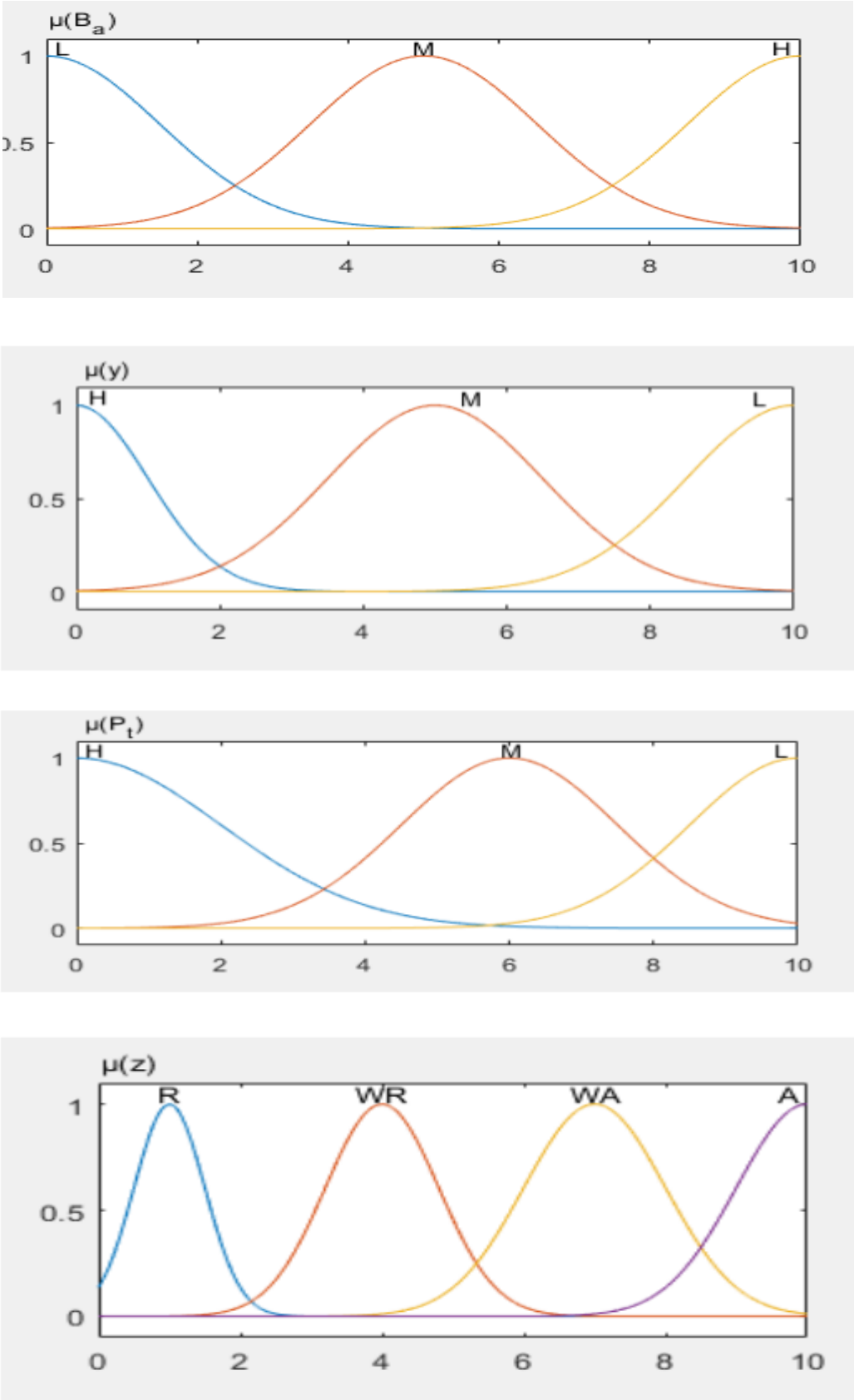


Figure 5. 5 Membership Function of Bay, Pt and z for type-2(Data)

5.4.1 COMPARISON OF FIGURE 5.4:

By comparing NFCAC model to the FLCAC policy in the NNCACAC scheme, we can see how well it performs under the QoS guarantee constraint in terms of cell-loss ratio (CLR), channel utilization, call dropping-probability (CDP), & call blocking probability (CBP).

Figure 5.6 displays the cell loss-ratios (CLR) of several call-admission control methods, including proposed NFCAC model, FLCAC, and NNCAC. For both kinds of traffic services, it keeps the promised quality of service level. There are five CAC policies, including the NFCAC, and Fig. 5.6 demonstrates how they use the system resource.

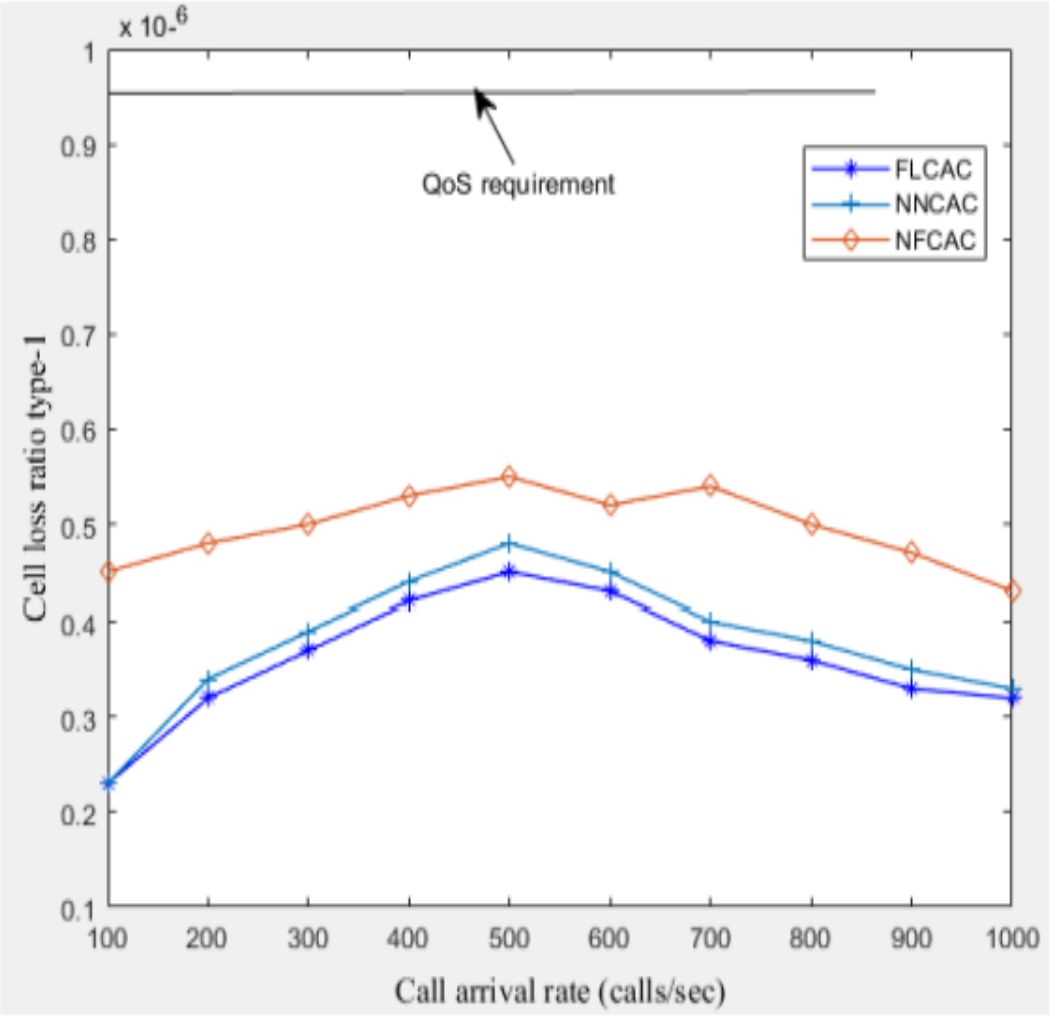


Figure 5. 6 Cell Loss Ratio for-Type-1 (Voice) Traffic

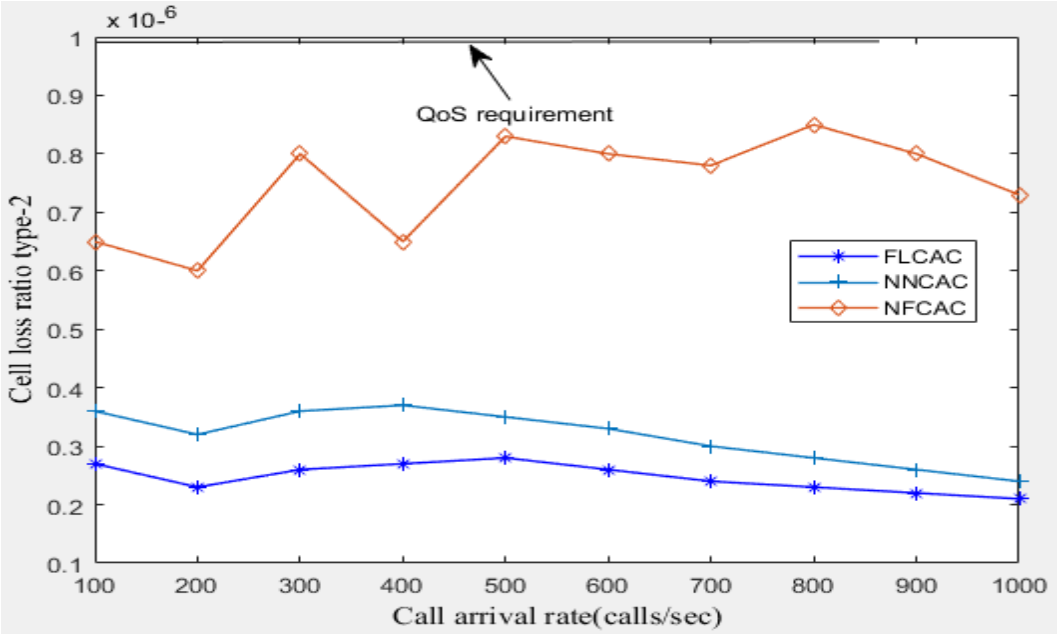


Figure 5. 7 Cell Loss Ratio-for Class-2 (Data) Traffic.

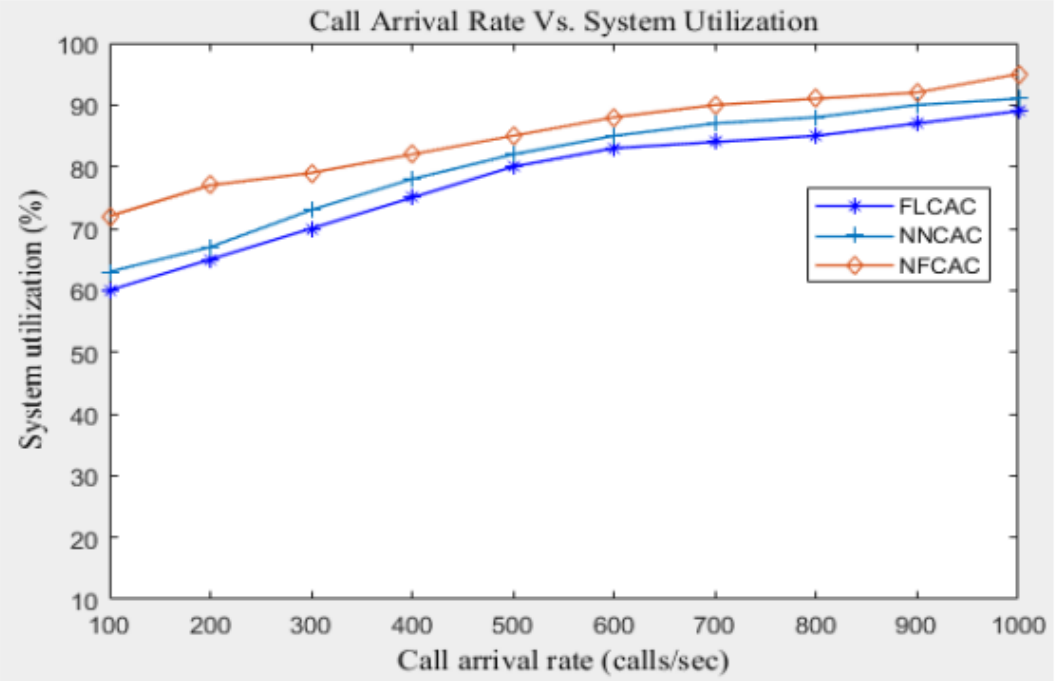


Figure 5. 8 System Utilization

The planned NFCAC has a greater proportion of system use compared to the NNCAC and FLCAC. Comparing NFCAC, NNCAC, and FLCAC, we find that 94%, 91%, and 89% of system is used, respectively.

Both real-time and non-real-time mobile network-services are shown in Fig. 5.9 and 5.10, which demonstrate performance of NFCAC under varying call arrival rates in terms of call-blocking probabilities. The results of simulation show that the two service classes have lower blocking probability compared to four CAC rules. Only when admittance requirements are in accordance with FIS regulations can the NFCAC system take on a new call.

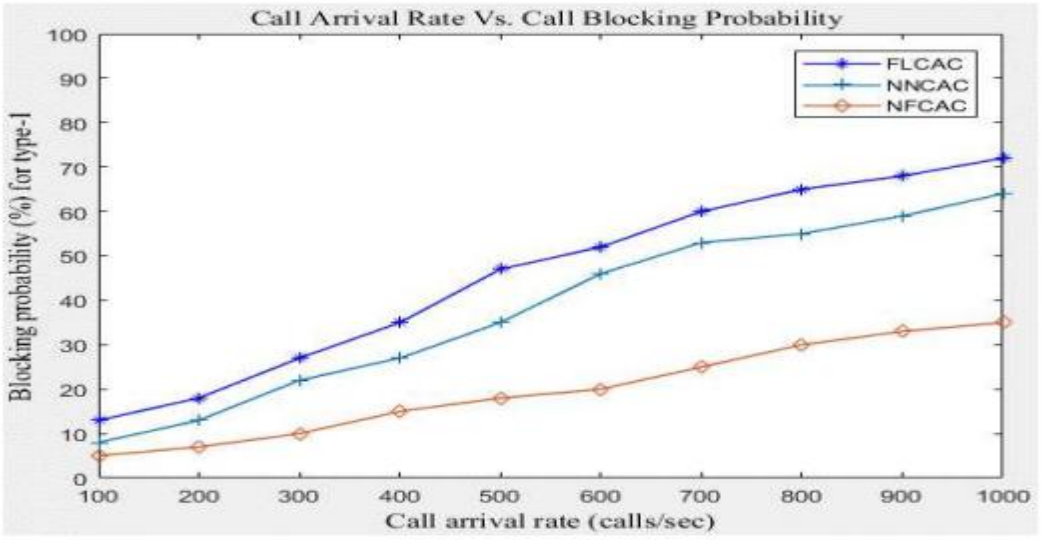


Figure 5. 9 Call blocking (%) for (a) class-1 (Voice)-traffic

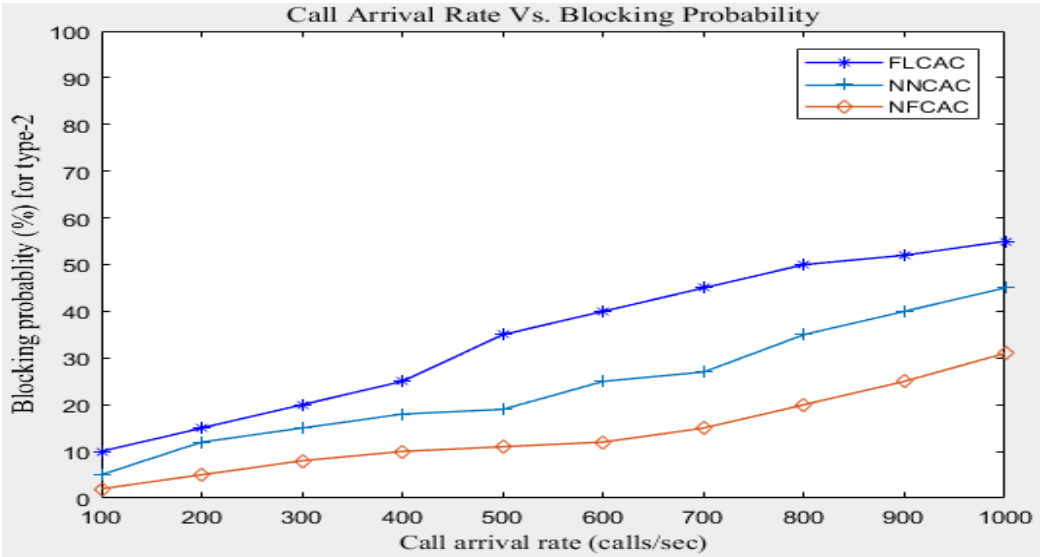


Figure 5. 10 Call Blocking (%) Class-2 (Data)-Traffic

The NFCAC-model yields a lower dropping probability in-both kinds of mobile-traffic compared to NNCAC, FLCAC, and schemes (Fig. 5.11 and 5.12). It has-been noted

after the simulation that dropping probability-percentage of NFCAC is less than 33%, while that of NNCAC is 39% and that of FLCAC is 39%.

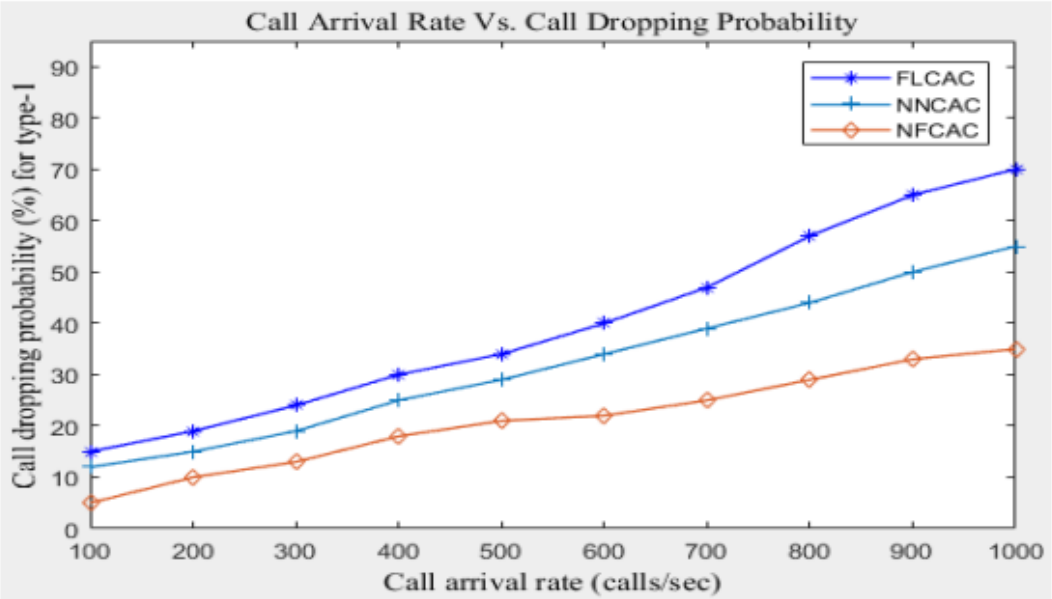


Figure 5. 11 Call Dropping (%) for Class-1 (Voice)-Traffic

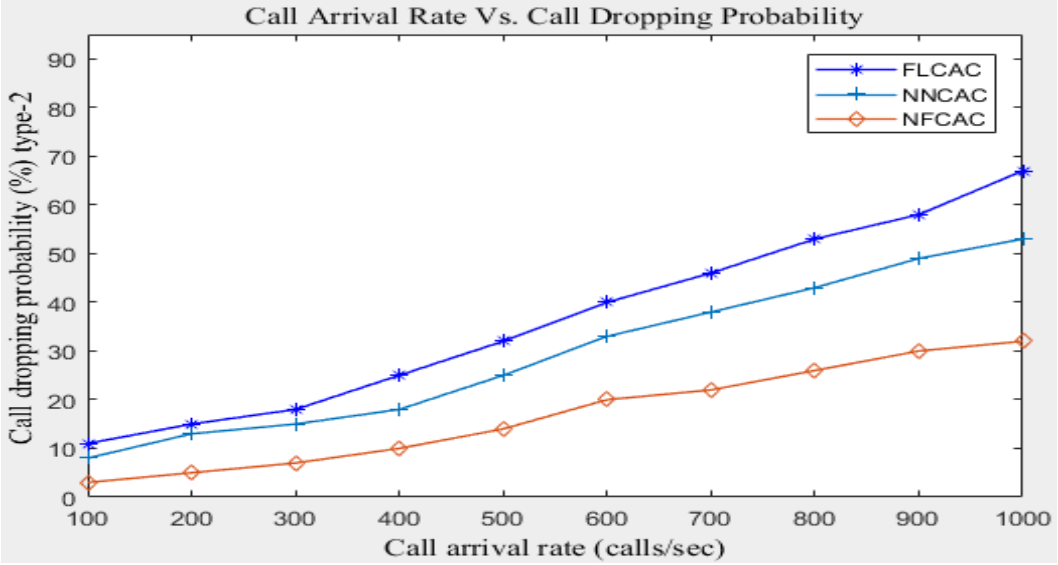


Figure 5. 12 Call-Dropping (%) for Class-2 (Data) Traffic

There are 200 iterations of the trials, a standard deviation of less than 5%, and training and test sets with identical sizes. For the type-1 and type-2 network classes, respectively, NFCAC requires 102 epochs of training, NNCAC 103 epochs, and FLCAC 105 epochs, as-shown in figures 5.13 and 5.14. Compared to FLCAC and

the NNCAC, the NFCAC learns more quickly. Although NNCAC & FLCAC both call for 150 and 480-weighting factors, respectively, this method reduces number of parameters used by NFCAC to 16.

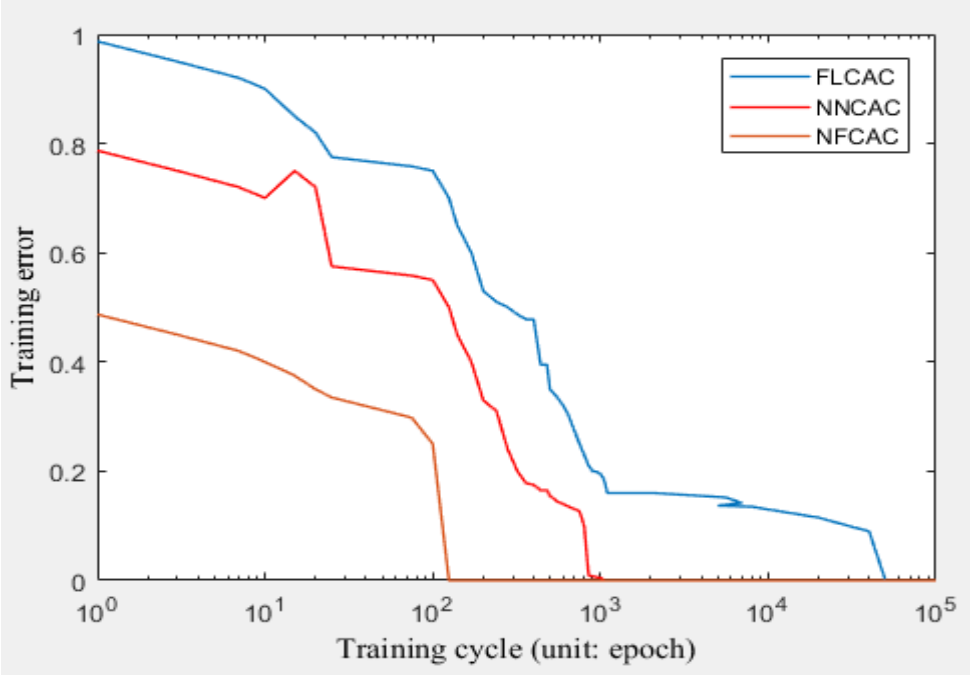


Figure 5. 13 Training Cycles Needed for-Type-1 (Voice)

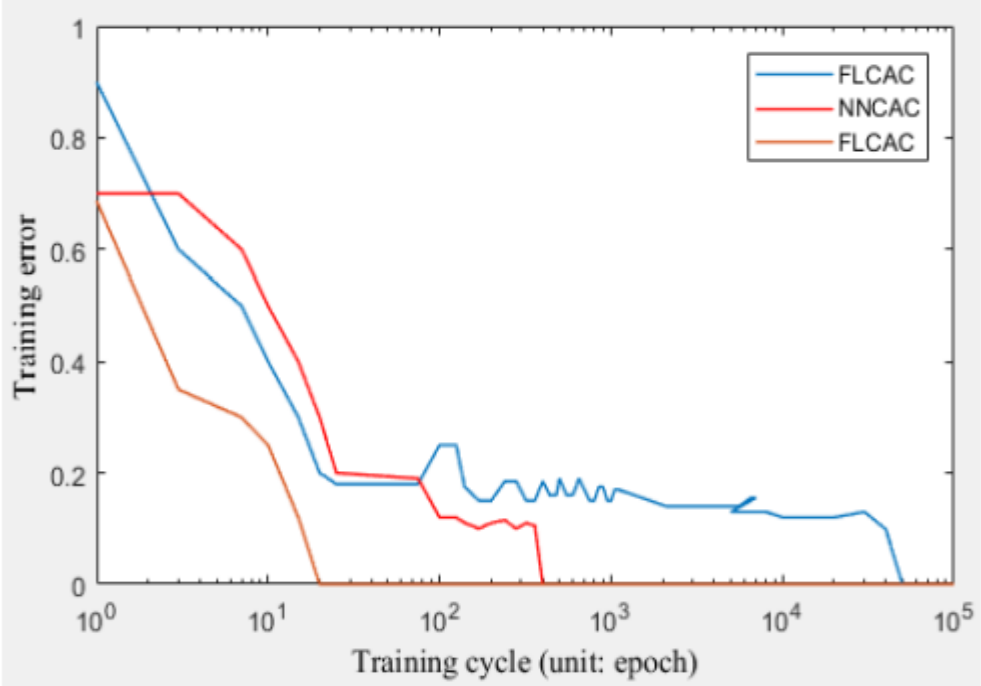


Figure 5. 14 Training Cycles Needed-for Type-2 (Data)

In this chapter, a model for high-speed mobile-multimedia networks called neural-fuzzy call admission control (NFCAC) was suggested. main objective of this integrated neural fuzzy-based CAC method is to reduce probability of call dropping and blocking in mobile-multimedia networks while maintaining quality of service by allocating the appropriate resources. The suggested neural-fuzzy CAC scheme is a hybrid method that uses a neural network's self-training capabilities in conjunction with fuzzy logic controller's semantic-control capabilities to build a computational-model for efficient traffic control & fair channel allocation for both new & handoff calls. This suggested NFCAC model makes use of a two-stage learning procedure. In phase one, fuzzy rules and membership-functions were constructed by a self-organized learning scheme. Phase two involved using a supervised-learning scheme to fine-tune membership functions to achieve desired-outputs in terms of call acceptance and rejection, all while maintaining QoS requirements at-different traffic loads. simulation results indicate that system utilization-percentage of NFCAC, NNCAC & FLCAC are 94%, 91% & 89% respectively. probability percentage for NFCAC is lower than that of NNCAC (39%) and FLCAC (39%).

CHAPTER 6
CONCLUSION

In the rapidly evolving landscape of mobile telecommunications, the integration of AI-powered Call Admission Control (CAC) systems represents a pivotal advancement in improving network performance. This technology's transformative impact can be understood through its multifaceted benefits, including enhanced resource allocation, improved quality of service (QoS), and more efficient management of network traffic. As mobile networks face increasing demands due to the proliferation of smartphones, IoT devices, and the emergence of 5G technology, need for intelligent and adaptive network management solutions has become-more critical than ever. AI-powered CAC systems leverage sophisticated algorithms and machine learning models to dynamically assess and predict network conditions, thereby making real-time decisions about admitting or rejecting new calls. Unlike traditional CAC mechanisms, which often rely on static rules and thresholds, AI-based approaches can adapt to changing network conditions and user behaviours. This adaptability is particularly crucial in handling varying traffic patterns, unexpected surges in demand, and the complex interplay of different types of network traffic. One of key benefits of AI-powered CAC is-its ability to optimize resource utilization. By analysing vast-amounts of data, such as historical traffic patterns, current network load, and user behavior, AI algorithms can make more informed decisions about resource allocation. This leads to more-efficient use of bandwidth, reduced latency, and minimized packet loss, thereby enhancing the overall user experience. Moreover, AI can help predict potential network congestion and pre-emptively manage resources to prevent degradation in service quality, which is essential- for maintaining high QoS standards.

The deployment of-AI in CAC also offers significant advantages in managing heterogeneous networks, which are common in modern mobile communication systems. These networks consist of various technologies and services, from traditional voice calls to high-speed data services and low-latency applications. AI algorithms can intelligently differentiate between these services, prioritizing critical applications and ensuring that resources are allocated according to specific needs of-each service type. This capability is crucial for supporting diverse applications, including real-time

gaming, video streaming, and critical IoT communications, each with unique QoS requirements.

Additionally, AI-powered CAC systems contribute to the scalability and flexibility of mobile networks. As networks expand and new technologies are integrated, such as 5G and beyond, the ability to seamlessly incorporate new services and manage increased traffic becomes essential. AI systems can learn & adapt to new traffic patterns and network configurations, providing scalable solution that can grow with the network. This scalability is not only vital for accommodating the increasing number of connected devices but also for enabling new use cases and business models in the telecom industry.

Despite these advantages, the implementation of AI-powered CAC is not-without challenges. One significant concern is complexity of developing and maintaining accurate AI models. These models require extensive training data and continuous updates to remain effective, as network conditions and user behaviours can change rapidly. Ensuring data privacy and security is another critical issue, particularly given the sensitive nature of communication data. Moreover, the integration of AI systems into existing network infrastructure requires careful planning and investment, as well as collaboration between network operators, equipment manufacturers, and software developers.

Looking ahead, future of AI-powered CAC in mobile networks is promising. As-AI technologies continue to advance, we can expect-even more sophisticated and efficient algorithms capable of-handling increasingly complex network environments. Future developments may include more advanced predictive models, capable of anticipating network issues before they arise and enabling proactive management strategies. integration of-AI with other emerging technologies, such-as edge computing and network slicing, offers further opportunities for optimizing network performance and delivering tailored services to users.

In conclusion, AI-powered Call Admission Control is a transformative technology with the potential to significantly enhance mobile network performance. By improving resource allocation, ensuring high QoS, and supporting the scalability of modern networks, AI-powered CAC systems are set to play crucial role in future of

telecommunications. However, realizing full potential of this technology requires addressing-several challenges, including model complexity, data privacy, and infrastructure integration. As telecom industry-continues to innovate, the deployment of AI-in network management will undoubtedly be a key driver of future advancements, ensuring that mobile networks can meet the growing demands of a connected world.

CHAPTER 7

RECOMMENDATIONS

The following recommendations are proposed for the study:

1. **Invest in Advanced AI and Machine Learning Technologies:** Mobile network operators should invest in state-of-the-art AI and machine learning technologies to develop robust CAC systems. This includes acquiring or developing advanced algorithms capable of real-time decision-making and predictive analytics. Emphasis should be placed on neural networks, deep learning, and reinforcement learning techniques, which can adapt to dynamic network environments & optimize resource allocation.

2. **Develop Comprehensive Data Strategy:** effectiveness of AI-powered CAC depends heavily on quality and quantity of data available for training and decision-making. Operators should establish a comprehensive data strategy that includes collecting, storing, and processing diverse data sets, such as traffic patterns, user behavior, and network performance metrics. Ensuring data privacy and security should be a top priority, adhering to regulations and industry standards.

3. **Implement Robust Testing and Validation Protocols:** Before deploying AI-powered CAC systems in live networks, rigorous testing and validation are crucial. Operators should develop simulation environments and testbeds to evaluate the performance of AI algorithms under various scenarios, including peak load conditions and network anomalies. Continuous testing and iterative improvements will help refine the AI models and ensure they perform reliably in real-world conditions.

4. **Enhance Collaboration Across the Ecosystem:** Collaboration between network operators, equipment manufacturers, software developers, and academic institutions is-essential for the successful deployment of AI-powered CAC. Joint research & development initiatives can lead to creation of more sophisticated and interoperable solutions. Additionally, partnerships with cloud service providers and AI technology firms can provide access to cutting-edge tools and platforms.

5. **Prioritize Scalability and Flexibility:** AI-powered CAC systems should be designed with scalability and flexibility in mind, capable of adapting to growing network demands and the introduction of new technologies, such as 5G and beyond. Operators should consider modular architectures that allow for eas- integration and upgrades, ensuring the CAC system can evolve alongside the network infrastructure.

6. **Focus on User Experience and Quality of Service (QoS):** The ultimate goal of implementing AI-powered CAC is to enhance the user experience and maintain high QoS levels. Operators should continually-monitor key performance indicators (KPIs) related to user experience, such as call quality, data speeds, and latency. AI algorithms should be fine-tuned to prioritize critical services and applications, ensuring that end-users receive the best possible service.

7. **Educate and Train Staff:** The deployment of AI technologies requires a skilled workforce capable of understanding and managing complex systems. Operators should invest in training-programs for their staff, focusing on AI and machine learning, data analytics, and network management. Continuous professional development will help ensure that team can effectively operate and maintain AI-powered CAC systems.

8. **Prepare for Regulatory Compliance:** As AI technologies become more prevalent in network management, regulatory bodies are likely to introduce new guidelines and standards. Operators should proactively engage with regulators to understand the evolving regulatory landscape and ensure compliance. This includes addressing issues related to data protection, algorithmic transparency, and ethical considerations in AI deployment.

9. **Explore Future Technologies and Innovations:** The field of AI and telecommunications is constantly evolving. Operators should stay informed about emerging technologies and innovations, such as edge computing, network slicing, and advanced analytics. Exploring these technologies can provide additional opportunities to enhance network performance and deliver differentiated services to customers.

10. **Engage with the Broader Community:** Engaging with the broader community, including users, developers, and researchers, can provide valuable insights and feedback on the performance and impact of AI-powered CAC systems. Operators should consider creating forums or platforms for community engagement, facilitating discussions and collaborations that can lead to further innovations and improvements.

By following these recommendations, mobile network operators can effectively implement AI-powered Call Admission Control systems, thereby enhancing network performance, optimizing resource utilization, and providing a superior user experience. This strategic approach will not only-improve current operations but also prepare networks for future challenges & opportunities in the ever-evolving telecommunications landscape.

CHAPTER 8

FUTURE SCOPE

The potential for further research into AI for Call Admission Control (CAC) in mobile networks is enormous and exciting, as AI and machine learning technologies continue to evolve rapidly in the telecommunications sector. With advent of 5G and beyond, the number and complexity of services, such-as IoT, autonomous vehicles, augmented reality, and smart cities, will require even more-advanced CAC systems. The potential of combining AI with edge computing and network slicing for ultra-responsive and personalized network management is an area for future research. Additionally, the potential for AI to predict and preemptively manage network congestion and outages could revolutionize the reliability and efficiency of mobile networks. Additionally, the ethical and regulatory considerations of AI in network management are gaining significant attention, with a focus on data privacy and algorithmic transparency. Future research in these directions could lead to more resilient, adaptive, and user-friendly mobile-communication systems that are able to satisfy the growing needs of a very connected world.

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Hopfield Neural Network for Dynamic Channel Assignment in Mobile Multimedia Networks

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ABSTRACT

To maximize coverage, cellular networks are often laid out in a hexagonal configuration, which consists of sets of continuous, non-overlapping cells. Channel reuse is essential for efficient management of limited frequency resources in mobile networks, and these cells form the basis of the geographic model for such networks. Nevertheless, network performance can be negatively impacted by co-channel interference, which is introduced by channel reuse. The fundamental motivation for this study is to discover a middle ground that may satisfy the demanding standards of mobile multimedia networks. To address this issue of dynamic channel allocation, the Hopfield Neural Network (HNN) is utilized. One type of artificial neural network, HNN updates neuron states and computes the weighted sum of inputs using auto-associative memory. By balancing hard and soft allocation strategies, the energy function of the HNN is used to optimize channel allocation in the mobile network, thus mitigating interference.

Keywords: Channel Allocation, Neural Network, Cellular, Multimedia

INTRODUCTION

A variety of services, including phone, video, gaming, and data communication, are made possible by mobile multimedia networks, which have become an essential component of today's telecoms infrastructure. The demand for mobile multimedia services has skyrocketed due to the widespread availability of smartphones, tablets, and other portable devices. Problems with resource management have become more apparent as a result of this increase in demand. The term "channel allocation" describes the procedure by which mobile customers are given specific channels to transmit data, video, or voice. Because of factors such as user mobility, bandwidth constraints, and the diverse quality of service needs of multimedia applications, channel allocation in mobile multimedia networks is notoriously difficult. Allocation becomes even more complicated when dealing with multimedia traffic, which is inherently dynamic and frequently demands low packet loss, low latency, and high data rates. As a result, satisfying users, optimizing network performance, and accommodating varied applications all depend on well-designed channel allocation algorithms.

The limited amount of radio spectrum is the primary obstacle to channel allocation. The amount of radio frequency spectrum available for use in wireless communication is a constraint. Because of the high data transfer demands of multimedia applications, efficient management of this limited resource is of the utmost importance. The goal of channel allocation is to enhance system efficiency, minimize interference, and maintain the needed quality of service (QoS) by assigning different users or devices within a network to different channels (frequency bands or time slots). Handling the available bandwidth, improving resource use, guaranteeing customer pleasure, and balancing trade-offs between system capacity and service quality are all aspects of this complex topic.

Centralized, distributed, and hybrid strategies are several ways to categorize dynamic channel allocation techniques. A single controller or base station handles channel allocation for the whole network in centralized DCA methods. Global resource optimization is possible with this approach, but it might not scale well, particularly in big networks with many users. Furthermore, the network becomes susceptible to compromise in the event that the central controller is compromised due to the single point of failure introduced by centralized systems. In contrast, dispersed DCA methods enable base stations or individual devices to autonomously allocate channels according to local data. Although this approach makes things more stable and scalable, it might not allocate resources optimally because it doesn't take global data into account. In order to strike a balance between centralized and distributed decision-making, hybrid methods integrate the best of both worlds.

Nevertheless, there are several difficulties with channel allocation in mobile multimedia networks. Because users are constantly on the move, there are a lot of handovers, in which devices migrate from one base station or access point to

another. Particularly for multimedia applications that are sensitive to delay, it is vital to ensure a solid connection and uninterrupted service during handovers. Poor channel allocation during handovers can result in buffering, dropped connections, and an overall worse user experience. In order to solve this problem, researchers have created predictive handover algorithms. These algorithms can tell when a user is going to leave a base station's coverage area and then pre-allocate channels in the next cell to make sure the transfer goes smoothly.

REVIEW OF LITERATURE

Mahmood, Maha et al., (2019) Because of the massive volume of data transmitted via the Internet, the area of Multimedia Information Retrieval (MIR) has become increasingly vital. Raw data or its components are two ways to describe multimedia data. Data structures having various properties, including images, music, video, and text, make up raw multimedia data. Semantic gap, or the discrepancy between how a notion is understood by humans and how it may be expressed in a language understood by machines, is the main obstacle to machine intelligence representation (MIR). Using a variety of algorithms through a two-stage process (training and testing) is the goal of this research.

Singh, Sunil & Vidyarthi, Deo. (2019) The cellular network architecture is the subject of much research on radio channel allocation. The nodes in the network must be careful with the limited resources known as channels. It is common practice for neighboring cells to lend or borrow channels during channel allocation. Only one lending or borrowing operation is used by the majority of the existing channel allocation algorithms. Cognitive radio has made it feasible to use the channels in an opportunistic way. The services that are available through the channels are typically categorized as either real-time or non-real-time. In this case, non-real-time services are given less priority than real-time ones. In addition, the new handoff services are prioritized above the call ones. By combining the concepts of cognitive radio with multi-channel lending/borrowing, this study suggests a new heuristic technique to improve channel utilization for these services. The suggested model's performance is evaluated by simulation, which shows the efficient use of channels in relation to dropped and blocked services.

Kumar, Sanjeev et al., (2016) Mobile multimedia communication systems have bandwidth constraints. However, channel allocation is essential for cell resource management and network optimization. This problem must be fixed to reduce blocked and dropped calls. This research introduces dynamic channel allocation using hopfield neural networks and handoff calls to move traffic. Enhancing the system's capacity. The Hopfield algorithm generates a new energy function that distributes incoming and outgoing call channels using traffic mobility data. We also investigated traffic mobility with an error-back propagation neural network model for intercell handoff calls and continuous service availability to improve QoS. Our system decreases call handoff dropping and blocking more than static or dynamic channel allocation systems.

Kumar, Sanjeev & Kumar, Krishan. (2014) One of the difficult difficulties with providing quality of service (QoS) in mobile multimedia network communication systems is call admission control (CAC). One definition of CAC is a system that limits access to a network depending on the resources that are available. If there are sufficient idle resources to meet the quality of service needs of the new call without compromising the quality of service for already approved calls, then the call is admitted. Otherwise, it is rejected. This article offers an overview of various CAC methods that are utilized in mobile multimedia networks. These schemes make use of soft computing techniques such as genetic algorithms, fuzzy logic, and artificial neural networks. Many factors utilized in mobile multimedia networks can be adjusted via soft computing. Our objective is to assess and contrast the most effective aspects of soft computing as it pertains to mobile multimedia networks in order to enhance the capacity of current CAC approaches. Additionally, this research delves into the future directions of artificial neural networks, fuzzy logic, and genetic algorithms, exploring their untapped potential. Topics covered include Genetic Algorithms (GA), Artificial Neural Networks (ANNs), Fuzzy Logic (FL), and Soft Computing (SC).

Omid, Moradi. (2010) Radio spectrum is a scarce resource in mobile wireless communication systems. But it has been demonstrated that the system capacity can be enhanced by the efficient utilization of existing channels. To enhance service quality while minimizing the likelihood of call blocking or dropping, a channel assignment system assigns channels to calls or mobiles in a certain way. It is well-known that channel assignment is an optimization problem that is NP-hard. A novel channel-assignment technique based on a tweaked Hopfield neural network is presented in this article. The channel-assignment problem is carried out via a modified discrete Hopfield network and is expressed as an energy-minimization problem. The algorithm determines an energy function and specifies the proper weights for the connections between neurons. When the constraint conditions are not met, each neuron receives inhibitory support from the interconnection weights, and when they are met, each neuron receives excitatory support. Seven benchmark issues with total frequencies ranging from 73 to 533 will be used to test the algorithm. All seven tasks were outperformed by this new method and its companions, the suggested regular interval initialization and updated interconnection weights.

Model of Mobile/Cellular Networks

The geographical model is likely comprised of a series of continuous, non-overlapping cells, as shown in Figure 1. All of these cells should come together to make a hexagonal parallelogram. A random selection is made at time t to

determine which cell will serve as the host and receive future calls. There has been no change to anything else in the entire network. The interference that happens when multiple channels are in operation at once is closely related to channel reuse, which is an inherent aspect of cellular networks. Less co-channel interference is an additional perk of a greater reuse distance. On the other side, with more cells ending up in each cluster, reuse efficiency decreases with increasing distance between reuses. So, when deciding on a frequency reuse pattern, it's important to think about how much co-channel interference there will be and how effective the reuse will be. The specification specifies the minimum reuse distance as the smallest normalized distance between cells sharing a channel. An interference zone radiates from the host cell in all directions. The cellular model considers the network's call volume at instant t instead of the initial conditions.

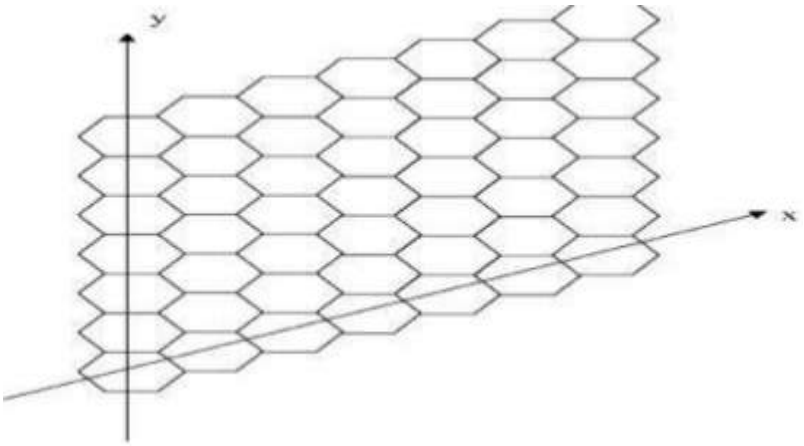


Figure 1: Mobile Network System

Representation Of The Problem

The proposed method considered least interference channel assignment. This challenge involves selecting a channel from a limited pool. The system with m cells has a solution M = 1,m2 mn}. C channels in the accessible frequency range have identical bandwidths.

O = c1, c2,... CMAX represents these channels' consecutive numbering.

Hopfield Neural Network

The late Dr. John J. Hopfield designed a Hopfield Neural Network (HNN) in 1982. Recurrent and totally connected networks exist. HNN depicts itself via auto-associative memory, another neural computing model. Additionally, HNN illuminate the human memory process. Artificial neurons are the fastest and easiest HNN construction method. The AI neurons' input capacity is N.

For every input i, weight wi exists. Additionally, they make something. No adjustments will be made to the neuron's output until new data arrives. The neuron is updated using these steps:

To complete the computation, it is necessary to calculate the weighted sum of all inputs, ∑i wixi, after determining their values, xi.

The weight value of each neuron can be approximated by combining the total inputs from several neurons with the threshold function.

The equation S = $wiba + xi$

The position of ab represents neural states.

The neuron threshold rule and threshold THD automatically update neuron states, as shown by.

$$v_i = \begin{cases} 1, & \text{if } U > \text{THD} \\ 0, & \text{otherwise} \end{cases}$$

Having more than zero weighted inputs sets the neuron's output state to one. When the weighted inputs are less than zero, use -1.

Neurons can keep their output state until updated.

$$y = \begin{cases} 1 & \sum w_i x_i \geq 0 \\ -1 & \sum w_i x_i \leq 0 \end{cases}$$

Formulation of HNN EnergyFunction

Energy function definition and explanation E shows that the HNN model may discover dynamic channel allocation issues.

$$E = \frac{1}{2} x^t\, Wx + b^t\, x$$

In HNN, "X" represents the input vector for channel assignment, "b" represents the velocity bias determined by constraints, and "W" is the symmetric weight matrix.

The DCA HNN model can design and describe the channel allocation problem. The literature review discusses DCA techniques and shows how an energy function can characterize the CPA in mobile multimedia networks with random mobility traffic load distribution. We developed a new energy function for mobile network DCA channel allocation.

This function allocates hard or soft channels.

CONCLUSION

In an era characterized by the increasing demand for varied multimedia services, channel allocation is an intricate yet critical procedure in mobile multimedia networks that guarantees the efficient use of limited resources. The continual development of mobile multimedia networks relies heavily on channel allocation. Future networks will need to incorporate safe, adaptive, and efficient channel allocation algorithms to meet the growing demand for bandwidth-intensive, real-time multimedia applications while keeping users happy.

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ASSESSING THE ROLE OF GUARD BANDS IN OPTIMIZING CALL MANAGEMENT IN CELLULAR NETWORKS

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ABSTRACT

Prioritization of new and handover calls is accomplished using the suggested model. It is presumed that the system follows a queuing strategy and reservation channel scheme to preserve the HO priority. This research looked at how guard bands affected the likelihood of new calls being blocked, the likelihood of HO calls being dropped, and the average waiting periods for new and HO real-time connections. Increasing arrival rates had a substantial influence on dropping and blocking probabilities, according to the findings. The guard band substantially reduced HO call drops by a factor of two to twenty compared to the scenarios without the band. Also, the data showed that a guard band reservation method did help with HO call handling, but it made new connections take longer to establish.

Keywords: Guard bands, Blocking, Real time, Probability, Call management

I. INTRODUCTION

The backbone of communication in today's hyper-connected world are cellular networks, which provide key services across many sectors, from personal communication to crucial corporate activities, and enable seamless interactions. An effective system for managing cellular calls is more important than ever before due to the explosion of data-intensive apps and the ever-increasing number of mobile devices. Improving call management entails fixing problems like call blocking and dropping rates while maintaining a good QoS for incoming and outgoing calls. Advanced algorithms, techniques for allocating resources, and cutting-edge technology are crucial in this setting.

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Managing call resources, especially during high demand periods, is one of the core difficulties of cellular networks. In order to decrease the blocking probability, which occurs when a user tries to begin a call but the system does not have enough resources, the system must utilize existing resources effectively. Users may become dissatisfied, churn rates may rise, and service reputation may suffer if blocking probabilities are high. Similarly, there are special difficulties with handover calls, which involve switching cells as users move around. Dropped connections during handover conversations may drastically diminish the customer experience if not handled correctly. If you want to keep your customers happy and stay competitive in the market, you need to make sure your call management systems can handle both new and handover calls.

Call management is affected by a lot of things, such how the network is designed, how much traffic there is, and how users respond. With smart resource allocation in response to real-time demand, a well-designed network can provide enough bandwidth for both new calls and continuing sessions. When users in a network have different expectations for the quality of service they get, dynamic resource allocation methods like priority-based queuing and reservation schemes come in handy for keeping everyone's needs met. One method that has been shown to drastically cut down on lost calls is the use of guard bands, which provide a certain amount of bandwidth just for handover calls. Nevertheless, it is important to consider the potential drawbacks of this strategy, such as longer wait times for incoming callers, while developing call management techniques.

Many network operators are looking at new technologies like AI and machine learning to improve call handling. In order to improve the overall efficiency of the network and allocate resources proactively, these technologies may examine past data in order to forecast traffic patterns. Networks may improve their reaction to changing traffic loads and, in turn, call management performance, by using algorithms that learn from previous actions. On top of that, analytics powered by AI can help with decision-making in real-time, so you can quickly change how resources are allocated according to user requests.

There are new possibilities and threats to call management brought about by the advent of 5G networks. The next 5G network is expected to completely transform the way we communicate by offering more faster data speeds, less latency, and more capacity. But, current call management procedures also need to be reevaluated in order to make the switch to 5G. Modern methods of call optimization are insufficient due to the complexity of 5G architecture, which includes support for mMTC and URLLC. An integral part of 5G, network slicing lets operators build several virtual networks on top of a single physical infrastructure, letting them allocate resources according to user needs. Network slicing allows operators to optimize call handling for various use cases, allowing for the optimal coexistence of both conventional voice services and developing apps.

II. REVIEW OF LITERATURE

Subramanian, Kanaga Suba Raja & Virgin Louis, Bamila. (2021) This literature review provides an overview of CAC methods in cellular wireless networks; more specifically, we highlight the relevance of CAC in the present day of communication and categorize it according to the research. This article presents a number of CAC scheme design considerations, investigates several CAC

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implementation approaches, and concludes by mentioning some research topics and difficulties related to next-generation wireless networks.

Singh, Avinash et al., (2018) The sudden increase in the demand from customers to make connections in a certain cell at the same time causes congestion, which is a common occurrence in wireless media. Cellular network traffic congestion is a common issue that has persisted through almost every generation. This is a daily challenge for all mobile network providers, and they haven't been able to find a solution yet. The growing number of people using cellular devices is driving up the need for more advanced gadgets, which in turn increases the bandwidth requirements of cellular subscribers.

Safwat, Mahammad et al., (2014) Optimizing the usage of assigned channels versus provided traffic while preserving the needed quality of service (QoS) is the job of the call admission control (CAC). It is difficult to provide quality of service to users at the cell edge when cell resources are limited because of inter-cell interference (ICI). Soft Frequency Reuse regulates how users share resources, which is one way to lessen the impact of ICI.

Senouci, Sidi-Mohammed et al., (2004) This article discusses the call admission control (CAC) issue in cellular networks that deal with various types of traffic that have varying resource needs. A semi-Markov decision process (SMDP) issue formulation is used for the problem.

III. EXPERIMENTAL SETUP

Simulation environment

We used Matlab, version 7.0.1, to construct our method. This program is selected because to its pre-installed foundation of features that are essential for simulating various traffic rules and queues. To generate traffic models based on random processes, functions like poissond and expond were invaluable (poissoniens, exponential, etc.).

For the purpose of representing the findings in curve form, other functions such as plot were also quite helpful.

Simulation parameters

The following assumptions and parameters were included into the simulation design:

- A homogeneous network has several cells, whereas this network only has one cell.
- Both the uplink and the downlink may use the full 10 Mbps of available bandwidth in the BS.
- Frame duration: 5ms.
- New and HO calls' arrival processes are poissonniens, with λ and μ being the corresponding parameters, and $\lambda = \mu * 5$.
- A duration of 200 frames is used for the observation.

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- Two kinds of traffic are taken into account here: video traffic encoded using MPEG-4 and file transfer protocol traffic whose flow ranges from 16 to 256 kbps. 5Kbps is the allotted minimum flow.

IV. RESULTS AND DISCUSSION

Impact of Guard Band on New Call Blocking Probability

We have recreated the BS's actions in relation to the new call arrival rates λ. Rates range from 25 to 45 calls per second (with HO call arrival rate: μ=λ/5) in both the G=0 and G=B/10 scenarios, where B=5Mbps. The two curves shown in Figure 1 are the results of the computation of the likelihood of new calls blocking:

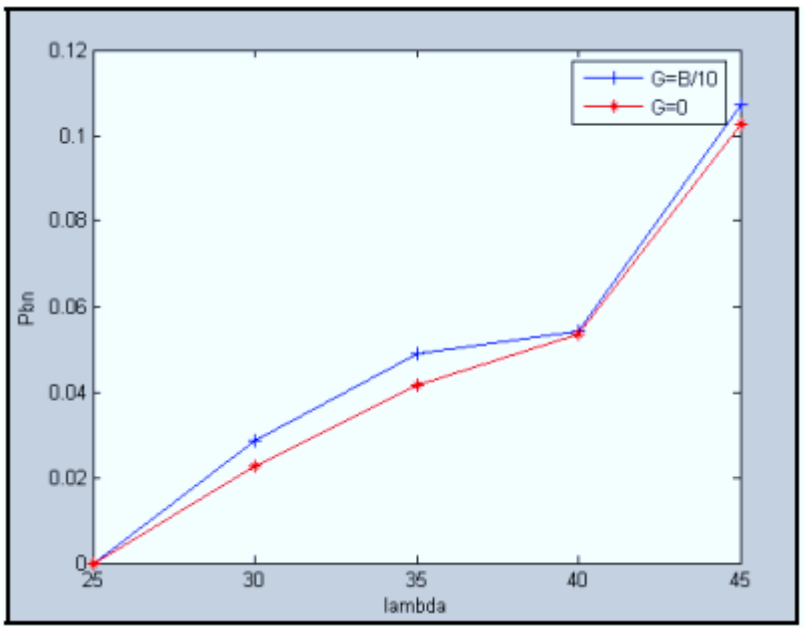


Figure 1: Impact of Guard Band on New Call Blocking Probability

The likelihood of new connections being blocked increases as λ (and by extension, μ) increases, as seen in Figure 1. The blocking rate is considered acceptable while κ is between 25 and 35 calls/s, ranging from 0 to 4%. However, when κ goes above these values, the blockage rate becomes too high, reaching over 10% when κ goes over 45 calls/s. In the first scenario, when G=0, the blocking rate is the lowest. This is understandable given that in this instance, both new and HO calls are handled equally: they are accepted if the bandwidth is available. As a result of allocating some bandwidth specifically for HO calls, the likelihood of new calls being accepted decreases, leading to an increase in the likelihood of calls being blocked, in the second scenario when G=B/10=500 kbps.

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Impact Of Guard Band on HO Calls Dropping Probability

Using the same settings as the previous paragraph, we have simulated the BS behavior to explore how the guard band affects the dropping likelihood of HO calls. Figure 2 displays the outcomes of the simulation.

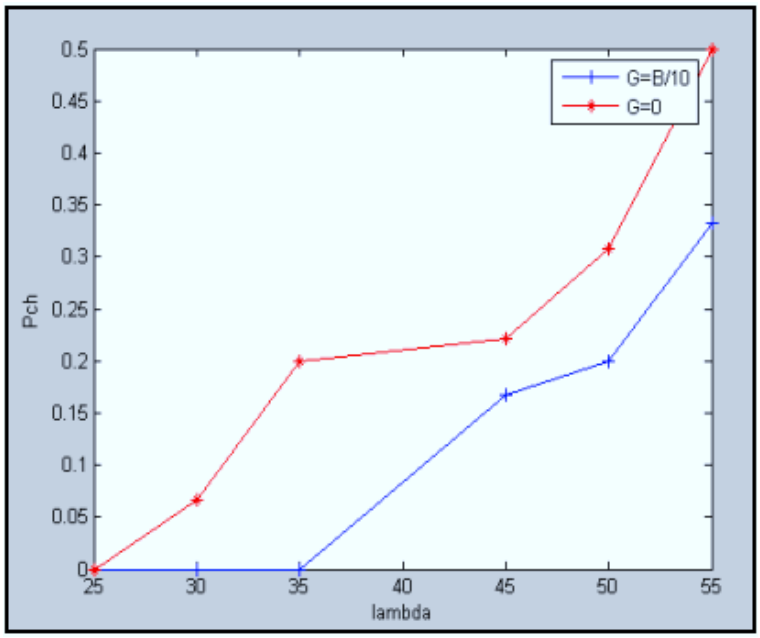


Figure 2: Effect of the guard band on the decrease in the likelihood of HO calls

As contrast to the policy without the band, which leads in a HO call dropping rate ranging from 2 to 20 times for an arrival rate Λ of 30 to 55 calls/s, we find that the admission control policy with the band significantly reduces this rate. The user has it bad when the Pch goes above 10% after 45 calls/s, which is terrible since losing calls is far worse than blocking them initially, and all HO calls are accepted up to 35 calls/s. We may experiment with parameter G to see what happens if we maintain this probability below a certain threshold for a high call arrival rate.

Protective Band's Effect on Typical Lag Time for New Real-Time Connections

Here, we suggest figuring out how long it typically takes for fresh real-time calls to be serviced in the queue. The following assumptions were made by us: There is a 40-millisecond limit on how long a real-time call may wait in the queue before being refused. This time is 10 milliseconds for HO calls. We got the following results (see Figure 3) by changing λ between 25 and 55 calls/s.

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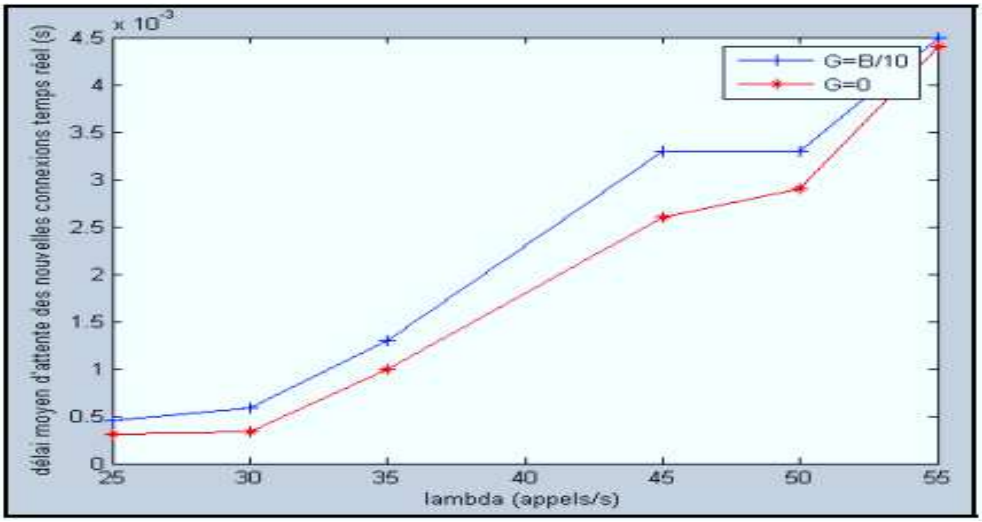


Figure 3: Impact of guard band on average waiting time of new real-time connections

The average waiting time for new real-time connections grows when the arrival rate of new calls and the guard band G both rise, as can be shown in Figure 9. New calls are more likely to be utilized with G=0 because they can take use of the available bandwidth. After that, they will wait in line, if not directly. If G is not equal to zero, means that some bandwidth is set aside for HO calls only, there might be available bandwidth that new calls can't use because it's reserved for HO calls only. This causes the call to wait in the queue and, if it goes over the maximum for the affected period, it might be rejected.

Impact Of Guard Band on Average Waiting Time of Real-Time HO Calls

This section will analyze the influence of guard bands on the average waiting time of real-time HO calls, using the identical assumptions as the previous paragraph. Two curves in Figure 4 were produced by the two scenarios when G=0 and G=B/10.

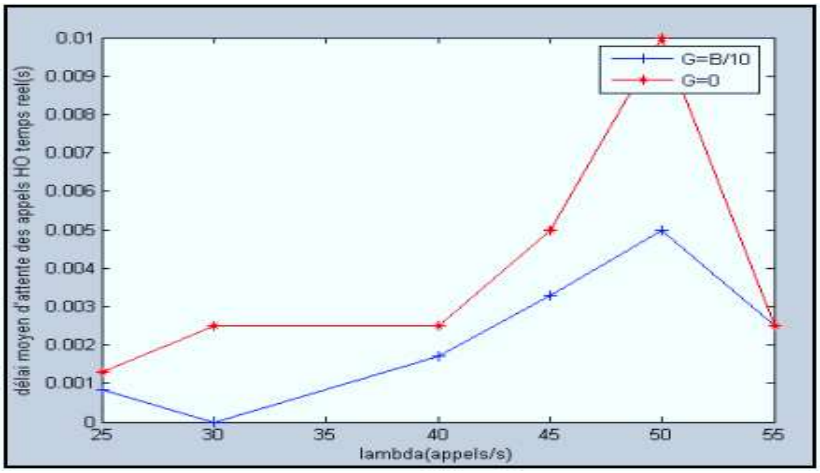


Figure 4: Impact of guard bands on average HO call wait times in real-time

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When comparing two entry control policies, one with and one without guard bands, in terms of real-time HO call handling, the former yields superior results (Figure 4). Due to the high time demand of these calls, it is critical to maintain the call waiting time before being given below a particular threshold whenever a request is made to migrate from one cell to another. Based on the statistics given in this image, our solution saves us about half the time compared to a policy without a guard band.

V. CONCLUSION

When compared to situations without a guard band, the testing findings show that HO call dropouts are reduced by a factor of two to twenty when a guard band reservation method is used. Results also show that waiting times for real-time connections and the likelihood of new calls being blocked both increase with increasing call arrival rates. While a guard band does improve HO call management, it unintentionally makes new call wait times longer, especially when bandwidth is set aside just for HO connections. The research concludes that in order to maximize the network performance, minimize user discomfort, and provide excellent service quality for both new and HO calls, a balanced approach is necessary when implementing guard band regulations. Improving the efficiency of call management in dynamic network settings might be the focus of future study, which aims to refine the guard band parameters to improve the trade-off between call admission rates and waiting times.

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Certificate of Publication

Dear Author(s) : Dr. Sunil Bhutoda

Professor, Department of Computer Science, P. K. University, Shivpuri, M.P.

It is indeed our pleasure to inform you that your Article titled:

Assessing The Role Of Guard Bands In Optimizing Call Management In Cellular Networks

has been published in our peer reviewed and referred International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) Volume 8, Issue 6, June 2025

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CERTIFICATE

This is to certify that Jyoti Balkrishna Patil, Research scholar, Ph.D. in computer science, P.K University, Shivpuri, M.P.

has presented a paper in **NCRASETHM-2024** held on **28th** January 2024 at Hotel Krishna Residency & Banquet, Noida, India.

Title of the paper A Study of Artificial Neural Network (ANN)- Based Channel Allocation in Mobile Multimedia Networks.

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National Conference on Recent Advances in Science, Engineering, Humanities, and Management (NCRASETHM - 2024)
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A STUDY OF ARTIFICIAL NEURAL NETWORK (ANN)-BASED CHANNEL ALLOCATION IN MOBILE MULTIMEDIA NETWORKS

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ABSTRACT

Artificial Neural Network (ANN)-based channel allocation in mobile multimedia networks is an advanced technique designed to optimize the use of network resources for delivering high-quality multimedia services. In these networks, efficient channel allocation is crucial due to the high demand for bandwidth and the need for low latency to support real-time applications such as video streaming and online gaming. ANNs, with their ability to learn from historical data and recognize complex patterns, offer a powerful solution to this challenge. By employing ANN algorithms, network administrators can predict traffic patterns, user behavior, and channel utilization more accurately. This predictive capability allows for dynamic and intelligent allocation of channels based on current and anticipated network conditions, ensuring optimal performance. ANNs can adapt to changing network environments by continuously learning and adjusting their models, which helps in managing the unpredictable nature of multimedia traffic and user mobility. This approach not only enhances the quality of service by reducing interference and congestion but also improves overall network efficiency. By integrating ANN-based channel allocation, mobile multimedia networks can better meet the demands of diverse applications and users, leading to a more seamless and enjoyable multimedia experience.

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Title of the Paper A study of Mobility - Driven context - Aware computing (CAC) for Resource Estimation in wireless Networks.

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25TH AUGUST, 2024

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A Study of Mobility-Driven Context-Aware Computing (CAC) for Resource Estimation in Wireless Networks

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ABSTRACT

Mobility-driven Context-Aware Computing (CAC) for resource estimation in wireless networks represents a sophisticated approach to optimizing network performance in dynamic environments. Traditional resource estimation techniques often struggle with the challenges posed by user mobility and varying network conditions. Mobility-driven CAC addresses these challenges by leveraging real-time context data, such as user movement patterns and network load variations, to enhance resource allocation and network efficiency. This method incorporates advanced algorithms that adaptively predict network resource requirements based on the current and anticipated movements of users, thereby improving the accuracy of resource estimation. By integrating context-aware computing, wireless networks can dynamically adjust resource distribution, reduce congestion, and enhance overall user experience. For instance, in scenarios with high mobility, CAC systems can anticipate network demands more effectively, leading to better handling of bandwidth and reducing latency. Additionally, this approach supports more efficient handoff mechanisms between network nodes, ensuring seamless connectivity as users move. Ultimately, mobility-driven CAC facilitates more resilient and adaptive wireless networks, capable of maintaining optimal performance despite fluctuating conditions and user behaviors.