Channel Allocation in mobile multimedia network using artificial neural networks

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***Abstract-** Capital asset control systems may enhance network performance, reduce congestion, and optimise resource allocation with the use of artificial intelligence. Using machine learning models like decision trees and neural networks allows for more informed and adaptive admission control options. These models can precisely predict how the network's quality of service (QoS) will be affected by accepting a new call. Exploring AI-enhanced CAC schemes requires a thorough analysis of various machine learning methods and their potential applications to real-time network management. To ensure that AI-based CAC implementations are actually possible in resource-limited mobile situations, it is crucial to consider their computational complexity and resource requirements. Accuracy and computational efficiency are two competing goals, and this study examines both. Finding a happy medium that can meet the stringent requirements of mobile multimedia networks is the driving force behind this research. Also covered in this study is the possibility of mixing AI-powered CAC with cutting-edge tech like 5G networks and cloud computing. Collectively, these technology and artificial intelligence (AI) have to open up new opportunities for situationally-conscious, dynamic admission manipulate. As a result, mobile multimedia networks might be a lot more efficient and adaptable. An exploration of CAC schemes is provided in this article, which draws attention to the potential game-changing impact of AI-based methods for mobile multimedia network optimisation. The increasing demand for multimedia services is creating new challenges, yet these challenges may be amenable to artificial intelligence integration into CAC systems. More adaptive and intelligent network management solutions would be possible as a result.*

***Keywords:** Channel Allocation, Mobile Multimedia Networks, Artificial Neural Network, quality of service, network management solutions.*

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INTRODUCTION

The number of individuals enthusiastic about multimedia and mobile communication has been rising steadily over the last several years. However, as there is a finite amount of usable bandwidth required for data and communication transmission between mobile devices and the mobile multimedia network's Base Station (BS), optimising bandwidth utilisation becomes an important consideration when planning bandwidth. Many people use the phrase "channel allocation" to characterise this problem. Finding the most effective distribution of available channels to every mobile in order to fulfill site visitors needs and channel constraints is the primary goal of channel allocation systems. This is the scheme's overarching goal. Ideal channel allocation is a pressing challenge because of the rising demand for mobile communication services and the confined frequency spectrum. Evidence suggests that Np complete optimisation is necessary for this particular situation. Numerous heuristic methods, including evolutionary algorithms, particle swarm optimisation, and neural networks, have been used to discover a resolution to this difficulty. It became clear throughout the assessment that some of the researchers have used HNN to create wireless communication-related applications. The majority of their frequency allocation solutions have been based on Fixed Channel Allocation (FCA) systems, which aim to minimise interference. A randomly selected cell model has had the idea applied to it. Based on that, this chapter's goal is to provide a novel and efficient dynamic channel allocation technique that uses Hopfield Neural Networks (HNN) to find a channel allocation that satisfies demand without causing any conflicts. The findings showed that the HNN could correctly lessen the decision rejection ratio, and the simulations method included four benchmark issues.

The dissemination, intake, and accessibility of data have all been profoundly affected by the meteoric rise of mobile multimedia networks. A primary problem in mobile multimedia networks is the effective distribution of channels, which has grown more important due to the explosion within the

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variety of smart devices and the exponential increase in data traffic. The introduction of smart and flexible channel allocation techniques is essential for meeting the developing demand for top-notch multimedia services like online gaming, video conferencing, and video streaming. Those techniques need to assure top performance while additionally fulfilling users.

Channel Allocation: A Difficult Task

Allocating presents frequency bands or channels to unique users and services in mobile multimedia networks is an vital part of channel allocation. The motive is to maximize network overall performance while minimising interference and keeping equitable access. Due to the inherent heterogeneity and constant change in today's mobile networks, traditional channel allocation techniques often use static or rigid algorithms. More complicated and adaptable solutions are needed to manage the complexity of many simultaneous connections, different quality of service (QoS) needs, and shifting network circumstances.

Problems with user heterogeneity, useful resource optimisation, scalability, interference control, quality of service (QoS), and converting network situations are just a few of the boundaries that mobile network channel allocation have to overcome. through studying and adapting to complicated patterns and making decisions primarily based on massive amounts of data, Artificial Neural Networks (ANNs) provide a potential approach to those problems.

Even in very unpredictable settings, ANNs can optimise channel allocation through continuously adapting to new network circumstances and user demands. They're ideal for programs that need speedy decisions due to how fast they can process and react to data from networks in real time. More effective and accurate channel allocation techniques are possible because ANNs may also examine from their research and enhance their standard performance over time.

Data collecting, network training, and real-time deployment are three important elements in implementing ANNs for channel allocation. user visitors patterns, community situations, and service needs are only some of the huge datasets that need to be collected throughout data series and preparation. The neural network is trained to understand patterns and forecast future network states using supervised analyzing strategies applied to previous records. Through integrating the trained ANN into the network structure, real-time deployment allows for the continuous tracking of real-time data and the dynamic allocation of channels in response to modern-day conditions.

The computational problem of training and deploying neural networks, the requirement for huge volumes of high-quality training information, and the risk for overfitting or underfitting are some of the remaining barriers. It is also important to assume cautiously about how to integrate ANNs with the protocols and infrastructure already in area for networks. Data needs, computational complexity, overfitting, underfitting, and integration with current structures are some of the current problems. For training to achieve success, you need large and varied datasets. For real-time performance, you want powerful hardware and efficient algorithms. For reliable results, it's important to avoid both overfitting and underfitting.

Neural Networks and Their Functions

One potential solution to the issues with channel allocation in mobile multimedia networks is using artificial Neural Networks (ANNs), that are modelled after the way the human brain operates. Artificial Neural Networks (ANNs) may study from facts and modify to changing network circumstances, in assessment to standard algorithms that regularly depend on static suggestions or heuristics. The ability to discover and recognize elaborate patterns in huge datasets is the basis of their flexibility, that is critical inside the ever-changing world of mobile networks. Keeping quality of service (QoS) and managing connections in mobile multimedia networks is becoming increasingly difficult as these networks manage more devices and more different applications. ANNs do very well in this setting due to their ability to analyse massive amounts of real-time data, spot patterns, and provide predictions, which allows them to distribute channels more effectively and dynamically. To reduce congestion and improve overall network performance, an ANN may, for instance, examine use trends in the past to foretell peak demand times and make proactive adjustments to channel allocations. In addition, ANNs can adjust to unforeseen events, including changes in ambient conditions impacting signal strength or unanticipated surges in user activity, and forecast future patterns thanks to their capacity to generalise from prior data. When making decisions quickly is crucial to keeping service quality high in real-time applications, this predictive capacity really shines. A vital tool for optimising network performance and guaranteeing a high quality of service for consumers, ANNs add a degree of intelligence and flexibility to channel allocation that is well-suited to the complex and frequently changing environment of mobile multimedia networks.

A Neural Network's Function

One potential solution to the problems with channel allocation in mobile multimedia networks is the use of Artificial Neural Networks (ANNs), which are modelled after the way the human brain operates. Automatic neural networks (ANNs) can learn and adapt to complicated patterns and make choices using massive amounts of data. Their capacity to draw conclusions from past data and foretell patterns makes them ideal for real-time and dynamic channel allocation jobs.

Channel Allocation Benefits from ANN Utilisation

- **Ability to adjust:** Even in very unpredictable settings, ANNs can optimise channel allocation

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by constantly adapting to new network circumstances and user demands.

- **Processing in real-time:** since of their parallel processing capabilities, ANNs are perfect for applications that need to make speedy decisions since they can analyse and react to network input in real-time.
- **Ability to Learn:** More effective and efficient channel allocation techniques are possible because to ANNs' ability to learn from previous mistakes and gradually increase their performance.
- **Recognition of Complex Patterns:** When it comes to managing the complicated interactions between various network characteristics and user behaviours, ANNs really shine at seeing nuanced patterns in data.

An Artificial Neural Network Approach to Channel Allocation

Several critical processes are involved in implementing ANNs for channel allocation, such as data collecting, network training, and real-time deployment. It all starts with gathering and preprocessing the right network data, such user demand patterns, channel utilisation statistics, and quality of service needs. Training the neural network with this data enables it to understand the interconnections and patterns.

Train the ANN, and then put it to work in the network to allocate channels based on real-time data. In order to maximise the ANN's efficacy, its performance is assessed using measures like throughput, latency, and user satisfaction. If necessary, more training and changes may be implemented.

LITERATURE OF REVIEW

Meghana et al. (2022) Neuronal networks and decision trees are examples of machine learning models that artificial intelligence (AI) may use to optimise resource allocation, minimise congestion, and increase network performance. By allowing a new call through, these models precisely predict how the network's QoS would be affected. Various machine learning methods and their use in real-time network management need to be thoroughly investigated in order to study AI-enhanced CAC systems. To guarantee their viability in environments with restricted resources, mobile AI-based CAC implementations must take computational complexity and resource requirements into account. The study also looks at the costs and benefits of computer efficiency vs accuracy. Finding a happy medium that can handle the rigorous requirements of mobile multimedia networks is the goal. New possibilities for dynamic admission control, enhancing the efficiency and adaptability of mobile multimedia networks, may arise from the combination of AI-driven CAC with emerging technologies such as 5G networks and edge computing. In order to address the increasing demand for multimedia services, this paper emphasises the revolutionary impact of AI on optimising mobile multimedia networks.

Gao et al. (2022) In order to meet the traffic needs of the user devices that are part of a WLAN, the network administrator must coordinate the usage of many access points (APs) and distribute limited radio frequency resources among them. In this research, we take a look at the WLAN channel allocation issue and propose a decentralised learning-based approach that minimises mutual interference across access points. We use the policy gradient approach to train GNNs model-free, construct the channel allocation issue as an unsupervised learning problem, and use graph neural networks (GNNs) to parameterize the control policy of radio channels. The suggested method is equivariant to permutations in the network and permits a decentralised implementation since GNNs are spread. Our method becomes independent of the AP reordering thanks to the latter, while efficient and scalable solutions for large network situations are provided by the former. The suggested technique is evaluated and theoretical conclusions are supported by empirical outcomes.

Chen et al. (2017) In a constantly changing world, next-gen wireless networks need to be able to handle a large number of IoT devices intelligently in real-time while also supporting very reliable, low-latency connectivity. To meet these demanding communication QoS standards and to implement mobile edge and core intelligence, it is necessary to integrate basic ideas of artificial intelligence (AI) and machine learning into both the wireless infrastructure and the devices used by end users. This article serves as an all-inclusive guide to machine learning, introducing readers to the fundamentals of ANNs (artificial neural networks) and their possible uses in wireless communications. A variety of important neural network architectures, such as feed-forward, recurrent, spiking, and deep neural networks, are covered in detail in this article. We outline the fundamental design and training process for each neural network type and discuss the potential and threats that come with it. We continue by outlining the many use cases for artificial neural networks (ANNs) in wireless communication, including but not limited to communication via UAVs, VR, and edge caching.We provide the primary rationale for using ANNs and the related difficulties for each application, illustrate them with a use case scenario, and outline potential future tasks that may be tackled with the help of ANNs. To sum up, this essay is one of the first comprehensive guides on creating machine learning methods for future wireless networks.

Kumar et al. (2016) The problem of restricted bandwidth is a major worry in mobile multimedia communication systems. Nonetheless, channel allocation schemes are crucial for managing the resources in each cell and maximising the network's available resources. As a result, this problem needs fixing so that fewer calls will be blocked or dropped.

Based on handoff calls and traffic mobility utilising a hopfield neural network, this research presents a novel dynamic channel allocation technique. The current system's capability will be enhanced. Using data on traffic mobility, the Hopfield technique creates a new energy function that distributes channels for both incoming and outgoing calls. In addition, we have investigated how well traffic mobility, supported by an error-back propagation neural network model, improves QoS in general with regard to intercell handoff calls and continuous service availability. When compared to other systems that use static or dynamic channel allocation, ours reduces the likelihood of call handoff dropping and blocking up to a greater degree.

AN ISSUE WITH CHANNEL ALLOCATION

The act of allocating a channel from a pool of available channels to a caller in a way that minimises interference while satisfying the requirements of the allocation matrix is called the Channel Allocation Problem (CAP).

- **Limited Capability of CAP-** The following [AUDH11] outlines the three main types of limitations that exist in the domain of mobile multimedia networks.
- **Limitation on Neighbouring Channels -** It is not feasible to assign the same channel to certain pairs of radio cells simultaneously, as per the Adjacent Channel Constraints (ACC) protocol. If you want to minimise the anti-correlation coefficient (ACC), you should arrange the channels in your cells so that their frequency distribution is as uniform as possible.
- **Inter-Channel Limitations-** The allocation of frequency spectrum to adjacent radio cells is not feasible when using Co-Channels next.
- **Limitation on Co-Sites-** A minimum frequency spacing between channels is the only requirement that may be satisfied for their use in the same cell.

Channel allocation in mobile multimedia networks is a problem that has inspired a plethora of heuristic approaches. These methods use genetic algorithms (GA), fuzzy logic (FL), artificial neural networks (ANN), and particle swarm optimisation (PSO) [SHRE16], [SHAR17].

The dynamic channel assignment (DCA) mechanism is introduced in this chapter, which is relevant to mobile multimedia networks. The challenges related to the optimal channel allocation have become more pressing as a result of the constrained frequency range and the increasing demand for multimedia services. However, in order to make the most of a system's available channels, a channel allocation method is crucial for handling the accessible channels in each cell.

A MODEL FOR MOBILE AND CELLULAR NETWORKS

Figure 4.1 shows what is presumably a set of continuous, non-overlapping cells that make up the geographical model. Collectively, these cells should form a parallelogram with a hexagonal shape. At time t, the host cell (the only cell that receives new calls) is chosen at random. Everything else in the whole network remains the same. Reusing channels is an inevitable part of cellular networks, and it's very related to interference that occurs when many channels are in use at once. Another benefit of a longer reuse distance is a lower degree of co-channel interference. Conversely, reuse efficiency drops as the distance between reuses increases, as more cells end up in each cluster. This means that the amount of co-channel interference and the efficacy of the reuse must be considered while choosing the frequency reuse pattern. The smallest allowed normalised distance between cells that may share the same channel is called the minimum reuse distance, and it is defined by specification. As a result, the host cell becomes the centre of an interference zone that stretches outward in all directions. The cellular model doesn't consider the initial conditions while it's running; instead, it considers the situation at an intermediate time instant t, when the network is presently supplying a certain quantity of calls.

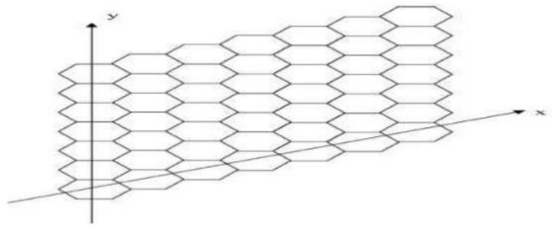

Figure 1: Mobile/Cellular Network Model

REPRESENTATION OF THE PROBLEM

The least interference channel assignment problem—which entails selecting a channel from a pool with a limited selection of available channels—was one of the issues considered by the proposed approach. The solution to the system with m cells is M = 1,m2 mn}. The available frequency spectrum is divided into an equal number of channels, C, with each channel having an equal bandwidth.

$\mathbf{O}$ = c1, c2,..., cmax} is the sequential numbering scheme used for these channels.

- **Solution for Channel Allocation Matrix and Vector-**

The total number of cells and channels in a network may be represented by the symbols M and a, respectively. In this specific network architecture, the channel allocation matrix is a matrix A with the dimensions $M \times a$ [VIDY05], [MORA11]. The symbol

$(i, b)h$ is used to represent the elements of this matrix.

$$A_{ij} = \begin{cases} 1 & \text{if channel } j \text{ is currently being used in cell } i \\ 0 & \text{otherwise} \end{cases}$$

$$\forall\, i = 1,2, \dots\dots, M, j = 1,2, \dots\dots C$$

Assume for the sake of argument that M=4, C=10, and that channels 3,4, 6, 1, and 3,7 are now in use in cells 1, 2, and 3, respectively. The newly-created channel allocation matrix is included below table 1.

Table 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

We are happy to confirm that cell k has received the updated call request and is now handling the [traf(k)-1] calls. In this context, "traf(k)" denotes the sum of all traffic loads in cell k at timest, whether incoming or outgoing. Around the whole system, no calls have been terminated and no calls are still outstanding. When it's possible to reassign channels to active calls in cell k, the difficulty is to provide the available channels to the incoming call instead of the current calls. A video from 2005. An appropriate configuration is a traf(k)-length vector of channel numbers, X, which represents a collection of channels allocated to the traf(k) number of calls received at cell k at the given time-instant.

If M=4, C=10, and V=[1 1 0 0 0 0 1 0 0 0] is an example of an acceptable arrangement, then the data on the new channel assignment in cell k is kept in a vector of length C with values of 0 and 1. With this in mind, we can see that V is a balanced function, or one-to-one, of X.

- **A Hopfield Neural Network-**

A kind of artificial neural network called a Hopfield Neural Network (HNN) was proposed by Dr. John J. Hopfield in 1982. These networks may be either entirely connected or recurrent. A further neural computational paradigm, HNN represents itself via its usage of auto-associative memory. Understanding human memory is also made easier with the use of human neural networks (HNN). Using artificial neurons is the simplest way to build an HNN [HOPF82]. There are a total of N inputs that these AI neurons can take in.

Each and every input i is associated with a weight wi.

They also produce something. Until the neuron is fed fresh data, its output will remain unchanged. In order to modernise the neuron, the following operations are carried out:

In order to complete the computation, we need to get the value of each input, xi, and then compute the weighted sum of all inputs, ∑i wixi.

It is feasible to approximate the weight value of each neuron, denoted by, by using the threshold function in conjunction with the total inputs acquired from different neurons.

$bi = wib\ ab + xi$

In where ab represents neuronal states

The neuron threshold rule and the threshold THD are used to update the states of each neuron naturally, as shown by

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

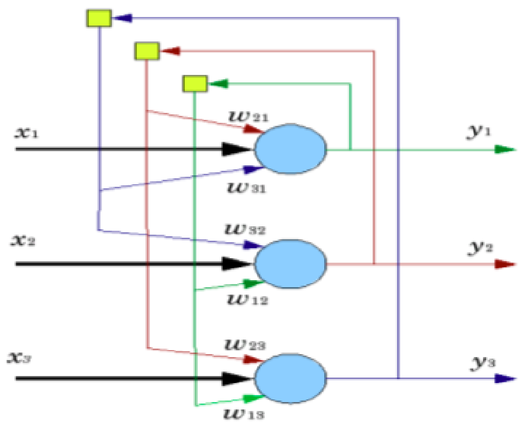

Figure 2: Architecture of Hopfield Neural Network

The neuron's output state is set to one if the sum of the weighted inputs is either higher than zero or equal to zero. When the sum of the weighted inputs is less than zero, the value -1 is applied.
The output state of a neuron may be preserved until it receives another update

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

- **The HNN Energy Function: A Formulation-**

The formulation of the energy function and its clarification In terms of identifying issues related to dynamic channel allocation, E proves that the HNN model is effective. The HNN energy function (E) has been the subject of several studies regarding its formulation, such as [LAZA00], [CALA06], [MORA11], and [PAND16].

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

Where

x is the channel assignment input vector;

b Velocity bias determined by limitations;

The HNN symmetric weight matrix, W.

By using the HNN model in DCA, the channel allocation problem may be formulated and captured. In mobile multimedia networks that experience random mobility traffic load distribution, the literature review details several DCA techniques and shows how the CPA may be described using an energy function. To address the difficulties of channel allocation in mobile network DCA methods, a new energy function has been developed. A representation of the strategy for allocating channels, both hard and soft, is this function. In [BATT01], [MONS09], and [SUBR12], we can see the energy or fitness function's formulation.

$$\begin{aligned} \boldsymbol{E} = {} & \frac{A}{2}\sum_{j=1}^{C}\sum_{\substack{i=1\\ i\neq k}}^{M}(V_{k},j\,.A_{i,j}.Interf(i,k)) + \frac{B}{2}\left[\sum_{j=1}^{M}(V_{k,j}) - Traf(k)\right]^2 \\ & -\frac{C}{2}\sum_{j=1}^{C}\sum_{\substack{i=1\\ i\neq k}}^{M}\left(V_{k,j}\,.A_{i,j}.\frac{1-Interf(i,k)}{Dist(i,k)}\right) \\ & -\frac{D}{2}\sum_{j=1}^{M}(V_{k,j}\,.A_{k,j}) + \frac{F}{2}\sum_{j=1}^{C}\sum_{\substack{i=1\\ i\neq k}}^{M}(V_{k,j}\;.A_{i,j}\,.[1-Res(i,k)]) \\ & +\frac{G}{2}\sum_{j=1}^{C}[Free_j\;.(1-V_{k,j})-H] \end{aligned}$$

in which

M Immature cells used by the apparatus.

C All of the system's accessible channels put together.

The sum of all currently accessible handoff guard channels is H.

If channel j is allocated to cell i, the elements of the allocation table will indicate 1, otherwise they will indicate 0.

The quantity of cells used when a call is either cancelled or arrived at. At cell i, you asked for the available channel, which is represented by Traf(i).

Cell of interest assignment, or Xk.

Dist(i, k) is the distance between cell i and k, which is an adjacent cell.

Interface between variables i and k In the event that a channel compatibility matrix is assigned a Unless explicitly stated otherwise, the channels in cells i and u cannot be compatible with one another.

If cells i and k are part of the same result pattern, then the channel reuse matrix, which is represented by the notation Res(i, k), has a value of 1, while otherwise it has a value of 0.

CONCLUSION

In order to optimise channel utilisation in mobile multimedia networks, this research aims to provide an HNN-based dynamic channel allocation model. Building an HNN model allowed us to evaluate the channel allocation problem. The evaluation of the model has been place across four benchmark problems. We found that a population size of 100 yields the greatest answer after testing the model with several other sizes. The Cell-Based Call Rejection Probability (CCRP) has been shown to be decreasing, and this tendency keeps getting worse with each repetition. This method converges much more rapidly with less iterations than other algorithms, including the Genetic approach (GA). Consequently, the wireless system would make better use of its channels and save time.

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