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Article

Millimeter Wave Massive MIMO Heterogeneous Networks Using Fuzzy-Based Deep Convolutional Neural Network (FDCNN)

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Abstract: Enabling high mobility applications in millimeter wave (mmWave) based systems opens up a slew of new possibilities, including vehicle communications in addition to wireless virtual/augmented reality. The narrow beam usage in addition to the millimeter waves sensitivity might block the coverage along with the reliability of the mobile links. In this research work, the improvement in the quality of experience faced by the user for multimedia-related applications over the millimeter-wave band is investigated. The high attenuation loss in high frequencies is compensated with a massive array structure named Multiple Input and Multiple Output (MIMO) which is utilized in a hyperdense environment called heterogeneous networks (HetNet). The optimization problem which arises while maximizing the Mean Opinion Score (MOS) is analyzed along with the QoE(Quality of Experience) metric by considering the Base Station(BS) powers in addition to the needed Quality of Service (QoS). Most of the approaches related to wireless network communication are not suitable for the millimeter-wave band because of its problems due to high complexity and its dynamic nature. Hence a deep reinforcement learning framework is developed for tackling the same optimization problem. In this work, a Fuzzy-based Deep Convolutional Neural Network (FDCNN) is proposed in addition to a Deep Reinforcing Learning Framework (DRLF) for extracting the features of highly correlated data. The investigational results prove that the proposed method yields the highest satisfaction to the user by increasing the number of antennas in addition with the small-scale antennas at the base stations. The proposed work outperforms in terms of MOS with multiple antennas.

Keywords: Multiple-input and multiple-output; quality of experience; quality of service (qos); fuzzy-based deep convolutional neural network

1 Introduction

One of the essential factors in the success of future wireless networks is ensuring that the user experience is as good as possible. For a massive MIMO heterogeneous network(HetNet), we investigate how to best allocate resources for the downlink based on the user's perception of the quality of experience [1]. Small cells can be found scattered throughout the network, in addition to macrocells, which are the most common type. A smaller number of antennas is used in small cell base stations (BS) compared to a more significant number of antennas used in macro base stations (MBS) [2]. Microcells and massive multiple-input multiple-output (MMaMIMO) technology, which are currently in development, have the potential to have a significant impact on future wireless networks [3]. When used in conjunction with large cells, multitier or heterogeneous networks (HetNets) have the potential to provide greater capacity than conventional homogeneous networks (conventional networks) [4]. Service quality of service metrics has been investigated by service and network providers to improve and optimize their networks and networks' performance.

When evaluating the quality of service (QoS) of a network, the emphasis is on measuring the network's technical performance rather than the experience of its users, which is a common practice [5]. According to the research findings, traditional quality of service criteria is insufficient for evaluating the user experience in virtual environments. Product or service perception is influenced by various factors, including technical and non-technical (human-based) aspects. The perceived end-to-end quality which is mentioned as the Quality of Experience (QoE), is essential when it comes to providing a better user experience (UX) for customers (QoE) [6]. The International Telecommunication Union (ITU-T) refers to the evaluation of an application or service by users in terms of its overall acceptability as the "quality of experience" (QoE). When evaluating the overall quality of an experience, both objective and subjective criteria can be used. Customers who have actually used a product or service are the ones who can provide the most valuable insight into how subjective methods should be improved. It is one of the most widely used and widely accepted subjective assessment methods, and it is known as the Mean Opinion Score (MOS) [7]. It is difficult, time-consuming, and expensive to conduct subjective quality of life assessments in real-time. Academic researchers have developed models for objectively evaluating quality of experience (QoE) which is based on the available quality of service (QoS) metrics. By incorporating measurements of the communication process into the objective quality of experience evaluations, a service provider's ability to estimate user satisfaction based on technical metrics can be improved. Experimentation and mathematical analysis were used to arrive at the equations, which were then refined. According to [8] experimentation is used to create models such as linear, exponential, or logarithmic functions, among other things, and to test them. The authors of [9] developed a MOS model that maps page response time to the quality of experience metrics by employing a Lorentzian function as a mapping function. They proposed a set of QoS parameters to model the way web browsing and video services are perceived by users of the respective platforms, which are based on their own experiences with them. The ability to support mobility means that millimeter wave systems can be used to benefit both vehicle communications and wireless virtual/augmented reality, as well as other applications. In order to train a neural network that predicts the beamforming vectors for each BS using the predicted beamforming vectors as input, it is necessary to use the predicted beamforming vectors as input [10]. It is now possible to use a portable millimeter-wave solution to provide reliable coverage with low latency and minimal training requirements. Because of the simulation results, it has been demonstrated that the proposed deep learning-coordinated beamforming strategy is just as effective as the genie-aided solution, which automatically generates beamforming patterns without the need for additional training [11]. It is possible for predicting the RF beamforming vectors of coordinating BSs by using only omnidirectional or quasi-omnidirectional patterns, which means minimal training overhead. This is the fundamental tenet of the solution that has been proposed. This manuscript is organized with Literature review in Section 2 along with the illustration of proposed work in Section 3. The performance is compared in Section 4 and the manuscript ends with a conclusive remark in Section 4.

2 Literature Survey

Traditionally, in wireless networks, predominantly in MaMIMO Nets, the measures for distributing resources to users and enlightening the network performance have been based on Quality of Service (QoS) parameters. In order to improve network parameters, it has only recently been proposed to look at the perception of Quality of Experience (QoE) (also known as Quality of Service) (also known as Quality of Service). When it comes to meeting user demand, it appears that QoE-based resource allocation is more operative than QoS-based resource allocation [12]. Few studies have demonstrated that this is correct. It was discovered that the Quality of Experience (QoE) metric, which can be used to optimize relay deployment in cooperative networks, can be used to optimize relay deployment. Users' quality of experience (QoE) is considered by the authors of [13], who propose a power distribution system for video streaming over wireless networks based on QoE. The authors provide an explanation of how to optimize aggregated MOS (mean of individual user MOS) in a heterogeneous network with a femtocell as a base station [14]. In order to maximize the accumulated MOS in cognitive radio networks, [15] proposes the use of beamforming in these networks. Researchers claim in their paper [16] that they are attempting to improve the quality of experience provided by MIMO cognitive networks (QoE). At this time, the quality of experience (QoE) might not been measured in the optimization of MaMIMOHetNets. When using dense mmWave systems, it has been demonstrated that multiple base stations can coordinate transmissions to all serve the same user at the same time [17]. According to studies, this will improve coverage while also reducing handover issues and complications. The Authors [18] used a frequency of 73 GHz to transmit a synchronized multi-point communication in an open square in the heart of downtown Brooklyn. The findings were published in the IEEE Transactions on Communications journal. When a large number of BSs served a single user simultaneously, the network coverage of coordinated mmWave beamforming improved significantly. The use of stochastic modeling tools enabled the researchers to reach their conclusions [18].

In heterogeneous millimeter-wave mobile networks, base station cooperation, in which multiple BSs serve the user at the same time, can result in significant coverage expansion, particularly in urban environments. The probability that a user is only connected to one or more LOS BSs was calculated and examined in the case of the example used in [19]. According to the researchers' findings, there should be a direct relationship between blockage density squared and the number of BSs that can maintain connectivity. They failed to investigate how coordinated beamforming vectors are typically associated with a substantial coordination overhead even though they demonstrated that coordination could result in significant coverage gains. Thus, the authors of this paper [20] set out to develop mmWave coordination strategies with low coordination overhead while still taking advantage of the increased coordination coverage and latency that mmWave technology provides. Due to this, mobile mmWave systems are difficult to operate due to the required training to operate large array beamforming vectors [21]. There has also been a surge in objective of producing directional antennas prediction systems to lower retraining expenses and boost effectiveness in recent times. It has previously been investigated whether beam training compressive channel estimation, and location-aided beamforming are effective techniques [22]. An exhaustive or adaptive search procedure can be used as part of the training process to select the most optimal beams for both the transmitter and the receiver. Given the requirement for all beams to be trained simultaneously, this technique is only suitable for transmissions with a single user and a single stream of information. A sparse reconstruction problem has been formalized as a channel estimation problem in mmWave systems, and space multiplexing has been demonstrated in mmWave systems using sparse channels [23].

2.1 Drawbacks of the Existing System

Compressive sensing techniques, which were developed specifically for this purpose, were required in order to accurately estimate the available parameters (angles of arrival as well as the departure, path gains) of the corresponding sparse channel, which were difficult to estimate otherwise. Even though compressed channel estimation based techniques which could reduce the intense training overhead, a significant amount of time is still required for the initial training phase [24]. On the other hand, exhaustive search solutions are significantly more efficient in the vast majority of cases, owing to the reduction in training time that occurs when the number of available antennas might increases. The practicality of this technique is in question because compressive channel estimation techniques rely on uncertain assumptions about the channel's exact sparsity and the quantization of arrival/departure angles, which are both subject to change. While using beamforming techniques in mmWave systems offers several benefits, the most significant is the ability to reduce training time by incorporating information from outside the operating band [25]. For compressive channel estimation, it was necessary to consider the relative positions of the transmitter and receiver. The sensor matrix was created with the assistance of this information. To construct beamforming vectors based on the position information presented in the papers, long-range mmWave backhaul and vehicular systems were utilized. According to [26], business specialists are in charge of vehicle systems, and they create a database that links the location of a vehicle to the results of beam training sessions. There are numerous benefits to utilizing this database for training purposes, including the ability to locate specific vehicles more quickly and efficiently. It is necessary to use only the location data that is available in order to create beamforming vectors. As demonstrated in solutions [27], which demonstrate that position information can reduce training overhead, this approach has several drawbacks. This may not be accurate enough for some applications, particularly those that call for GPS in conjunction with narrow-beam technology (such as astronomy). In the first place, these solutions cannot be used for indoor applications because Within structures, GPS sensors need not work properly. Beamforming matrices aren't only a reflection of the transmitter as well as receiver's spatial arrangement. but are also influenced by the geometry of the environment, obstructions, and other factors. In an NLOS environment, there may be multiple beamforming vectors available depending on factors such as the location of obstacles. As a result, location-based beamforming solutions are the most appropriate solution type in a LOS environment.

3 Proposed Method

In this work, the various issues in handling the millimeter-wave band are analyzed. The main problem faced is the attenuation loss which occurs due to the usage of the high frequencies. It is compensated by using the massive array of structured MIMO with heterogeneous networks. The optimization problem is also tackled here. The flow of work corresponding to the proposed model is shown in Fig. 1.

Here the MOS, QoE, and QoS are considered the metric for dealing with optimization-related problems. In order to handle the complexity-related issues, the DRLF is implied along with FDCNN.

3.1 MIMO (Multiple-Input and Multiple-Output) and Heterogeneous Networks (HetNet)

The occurrence of attenuation losses might be compensated with MIMO and HetNet. Here a modified massive array structured MMaMIMO with HetNet which consists of C_s small cells which could be prearranged in the area of short coverage regions of the macro cell is shown in Fig. 2.

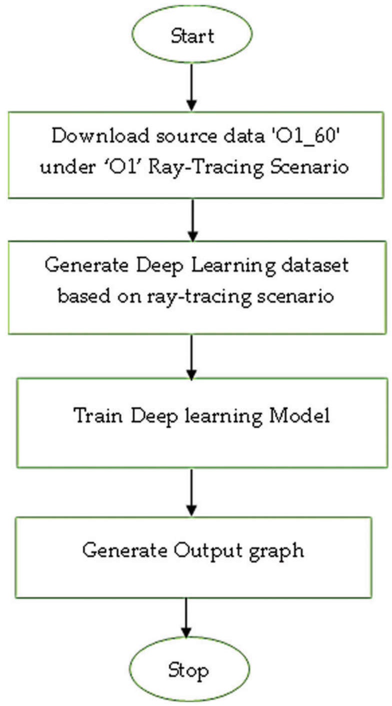

Figure 1: Flow of the proposed model

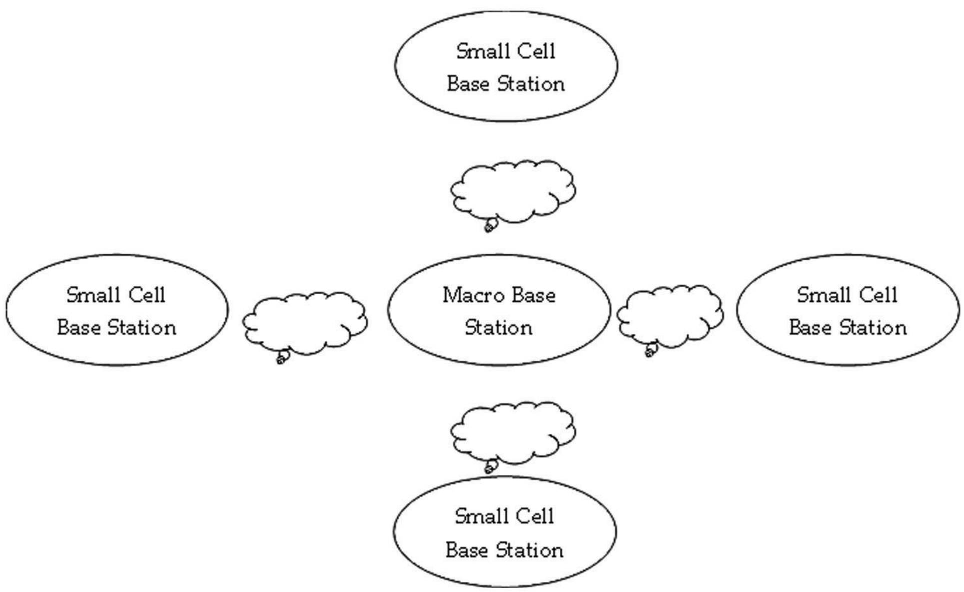

Figure 2: MMaMIMO with HetNet which consists of $C_s$small cells

The macro base station (MBS) along with the small cell base station (SBS) might use the non-coherent transmission that are coordinated with multipoint beam forming are used for providing the services related to video or internet browsing for Q antenna users. Here MBS along with SBS involve in transferring the valuable information's to the users and the individual base stations (BS) send their own separate stream of data. The macro base stations are having R antennas and hence R >> Q. The total number of available antennas at the k^{th} SBS is mentioned as N_k. The received signal at user U_1 is mathematically expressed as

$$\chi_u = {f_{u,0}}^F Y_0 + \sum\nolimits_{k=1}^{r} {f_{u,k}}^F Y_k + \sum\nolimits_{j=1}^{\alpha} n_j \tag{1}$$

The macro base stations along with the small cell base stations might be connected to the available network which enables the soft cell resource allocation for non-coherent non-linear transmissions by serving the individual transmitters with coded information sysmbols which is emitted independently.

The information symbols which could be taken from the base station and the k^{th} SBS to the user U_1 is represented with $a_{i,0}$, $a_{i,j}$ respectively which is originated from the separate gaussian elements from the unit power which is represented by $a_{i,j:TZ(0,1)}$ for j = 0,…,S. The available resources are correlated with the vectors representing the beamforming section represented with $\omega_{j,0} \in M^{H_{BS}\times 1}$ and $\omega_{i,j} \in P^{H_{SBS}\times 1}$ for obtaining the transmitted signals which is represented by

$$\alpha_j = \sum_{i=1}^{\infty} \omega_{i,j} \times \alpha_{i,j}, \;\; j = 0, \ldots, S \tag{2}$$

The corresponding vectors for beamforming are represented by optimizing the needed variables which is mentioned in this paper. The elements $\omega_{k,j} \neq 0$ is made available only for the possible transmitters 'I' which intentionally serve the user U_1. The assignment related to the transmitter is gathered automatically from the optimization problem solved earlier.

3.2 Mean Opinion Score (MOS) vs. QoE(Quality of Experience) vs. Quality of Service (QoS)

The MOS is considered as a measure of qualitative data for assessing the QoE and QoS that might be signified in terms of the impartial mathematical restrictions. The relation which is considered experimentally in between the QoE in addition with the QoS is articulated mathematically as given in Eq. (3).

$$MOS^{Int} = T_1 \ln(s_1(R)) + T_2 \ln(s_2(R)) \tag{3}$$

Here the constants T_1 and T_2 are selected to bring the MOS (internet) value to be in the range 1 to 10. Additionally, $s_1(R)$ and $s_2(R)$ represent the response time of the page or the delay that exists in between the web page request and the reception of the search contents. $s_1(R)$ and $s_2(R)$ might depend on the parameters representing the size of the web page, the total round trip time and the various types of protocols that are used might be expressed as

$$s_1(R) = RKK + \frac{IS}{BW} + L_1\left(\frac{SS^{max}}{BW}()\frac{2SS^{(\max)}(2^{L_1}-1)}{BW}\right) \tag{4}$$

$$s_2(R) = RKK + \frac{IS}{BW} + L_2\left(\frac{SS^{max}}{BW}()\frac{2SS^{(\max)}(2^{L_2}-1)}{BW}\right) \tag{5}$$

$$s(R) = RKK + \frac{IS}{BW} + [L_1 + L_2]\left(\left(\frac{SS^{max}}{BW}()\frac{2SS^{(\max)}\left(2^{[L_1+L_2]}-1\right)}{BW}\right)()\right) \tag{6}$$

where IS[bit] represents the internet web page size and BW[Hz] represents the bandwidth in hertz and SS[bit] represents the segment size, where the maximum values is taken. Here L is represented as L = min[L_1, L_2], which is observed as a parameter that characterizes the number of slow start cycles which is considered as the ideal periods.

The values of L_1 and L_2 is represented using the formula

$$L_1 = \log_2\left(\frac{1}{2} + \frac{RKK}{SS^{max}}()_2 \log_2\left(\frac{1}{2} + \frac{RKK}{2SS^{max}}()\right)\right) \tag{7}$$

Then the services related to the video is considered for calculating the MOS value and is represented as

$$MOS^{video} = b\log(PSNR) + e(n) \tag{8}$$

where b and e are considered as the two available coefficients which is nominated in its own way that the representing value corresponding to the MOS(video) might get fall in the specified range from 1 to 10. The PSNR value is mathematically noted as

$$\text{PSNR} = \alpha + \beta\sqrt{\frac{\text{B.R}}{\gamma}\left(1 - \frac{\gamma}{\text{B.R}}\right)} \tag{9}$$

where α, β, and γ are the parameters required for categorizing the explicit video stream. The sub channels that is available in between the users and the SBS or MBS is demonstrated as flat fading channels.

The channel exists between the i^{th} user along with the j^{th} user in SBS is expressed by $h_{i,0} \in H^{N\times 1}$ *and* $h_{i,j} = H^{N_j\times 1}$. Here it is considered that there exists some critical information's available at the base station. The signal which is transmitted from the MBS and the SBS are mathematically expressed as $\alpha_0 \in H^{N\times 1}$ *and* $\alpha_j \in H^{N_j\times 1}$. The signal which is received at the i^{th} user is mathematically expressed as

$$\chi_i = h^{H}{}_{i,0}X_0 + \sum\nolimits_{\substack{i=1\\ j=1}}^{n_s} h^{H_1}{}_{i,j}X_j + \sum\nolimits_{\substack{i=1\\ j=1}}^{n_s} h^{H_2}{}_{i,j}X_i + n(i,j) \tag{10}$$

where $n(i,j) \cong \text{ZK}(0, \sigma_i{}^2)mW$ is considered as the additive white gaussian noise (AWGN) marked at the receiver. The transmitted signals X_0, X_i is attained in order to apply the appropriate corresponding vectors at the base station is mathematically expressed as

$$X_i = \sum_{l=1}^{\tau} \text{Z}_{l,i}s_{l,i} + \sum_{i=0}^{\infty} w(i,0) \tag{11}$$

where $w_{l,0} \in \text{H}^{M\times 1} and w_{l,j} \in \text{H}^{M_j\times 1}$, j = 1,2,….n represents the beamforming vectors mentioned at the MBS in addition with the SBS which will corresponds to the l^{th} user and $s_{l,j}$ is considered as the information symbol which is transmitted to the base station.

3.3 Fuzzy-Based Deep Convolutional Neural Network (FDCNN)

Fuzzy based deep convolutional neural networks (FDCNN) which have been exposed to ensure efficient and effective use of the temporal aspect of data in addition to simulating nonlinear relationships in input data. In millimeter wave communication the base station (BS) or the access points are concurrently serving the mobile station (MS). Here one mobile station is used and four base stations are used. The BS is fortified with 'N' antennas and the corresponding BS is connected to a centralised processing unit as shown in Fig. 3.

Each base station has only one chain containing radio frequency and when it is applied to the analog communication link i.e., the beamforming-based networks with a change in phase shift. The extension for pertaining the more sophisticated millimeter wave architectures is analysed at the base station. The channel data might contain all needed information's related to the beamforming section. The main aim of the FDCNN is to excerpt the valuable needed features from the available data. The information gathering is from video signals and some internet page contents. The collected contents are then detected, compressed and filtered for forming the contents for segmentation. Totally two different outputs are obtained one with the segmented image and other with the convoluted image. Here the mobile user is having a solitary antenna, where the designed algorithms along with the possible solutions are protracted to the multi-antenna users.

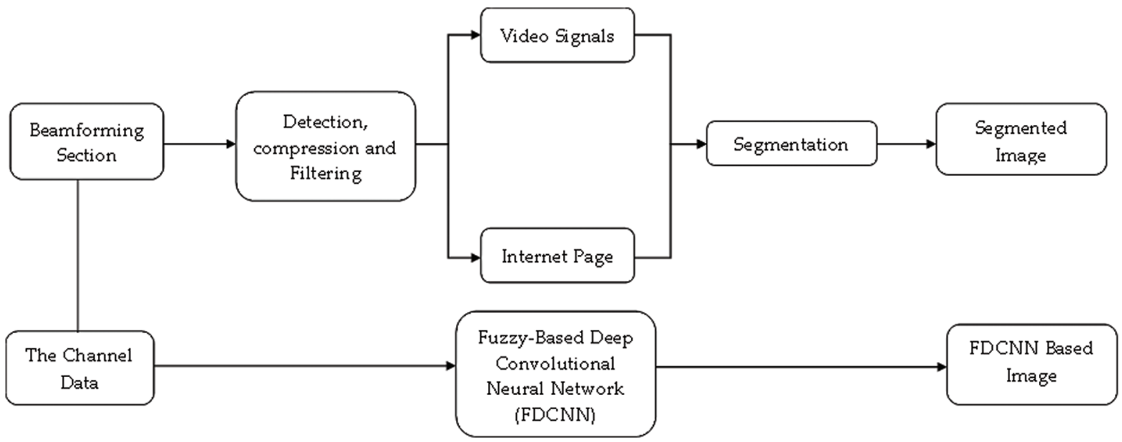

Figure 3: Proposed FDCNN model

Considering the down link related transmission, the available antenna data symbol $d_s \in \mu$ taken at the sub carrier C = 1,2,….c. this is initially precoded by using the N × M digital precoder shown in Eq. (12).

$$f_k^{\alpha\beta} = \left[f^{\alpha\beta}{}_{k,M}, \ldots.., f^{\alpha\beta}{}_{k,N}\right]^R \tag{12}$$

The final output is obtained from the resulting symbols which is transmuted to time domain in order to use the possible n-numbered K point inverse Fourier transforms. The cyclic prefix code is added to the blocks of the symbols before moving it back to the base stations by using the wired or optical fiber channels. Each BS is applied to the analog beamforming section and the obtained resulting signal is transmitted. The discrete time signal which is transmitted ro the base station is taken at the k^{th} subcarrier and is expressed as

$$X_{r,n} = f^{rf}{}_n + f_{r,n}{}^{CP} d_r \tag{13}$$

Here the transmitted signal which is assumed to be $E[d_r d^T{}_r] = \frac{T}{R}$, where the T is the total transmitted power. The radio frequency is considered for the beamforming part which is assumed to be implemented by using the FDCNN by the form of quantized angle. The sub carrier which is adopted by the transmitted power is defined in order to satisfy the radio frequency based beamformers as shown in Eq. (14).

$$\|F^{RF} f^{CP}{}_r\|^2 = 1 \tag{14}$$

4 Experimental Results

The downlink procedure of the HetNet (5G) is examined in this part, which involves a macro cell with an approximated radius of 350 metres and four tiny cells with a radius of 50 metres that are installed in the precise location. The four chosen SBS are evenly placed within a radius of 100 m centred at MBS. If a scenario with eight users in the macro cell and one user in each tiny cell is supplied, where the total user is (U = 12). The users are made to distribute uniformly by covering the area within the radius of 50 and 350 m for the individuals who use the macro cells and each user uses one cell (small cell). considerably all the SBS is assumed to have equal number of antennas and hence $N_c = N$, for all values of c ranges from 1 to n. The powers consumed by all the antennas are noted to be 14 dbm for MBS and −9 dbm for SBS. The proposed work is analyzed using Network Simulator-2 (NS-2) tool.

The band width of the subcarriers is marked to be 12 kHz. The penetration loss and the path loss is noted at a distance of 's' km taken in between the MBS and SBS. This distance for MBS is marked to be $136.54 + 23 \log_{10}(s)$ dB and for SBS it is marked to be $112 + 27 \log_{10}(s)$. The standard deviation is considered to be 10 dB for log-related shadow fading. The small-scale fading part of the channels is designed by considering the separate Rayleigh variables. Here the results obtained for the different services which is offered for the browsing related to intense and the video signal related information taken out separately. The major parameter considered for analyzing the proposed work is the Average MOS for which the different antennas were used, and the performance is compared with existing methodologies.

4.1 Internet Page Browsing

For services related to the intenet browsing the number of users are assumed to be from 1 to 8, individually for accepting the page sizes of the website with 50, 100, 150, 200, 250, 300, 350 kB. Let us consider the minimum spectral efficiency and maximum spectral efficiency for individual users are limited to 2 bits per seconds to 10 bits per second. T_1 and T_2 is obtained by considering the MOS value as minimum to R minimum and then the maximum to the R maximum which delivers the output value $T_1 = 4.432$ and $T_2 = 12.876$.

The Fig. 4 illustrates the total number of HetNet MBS antennas available in the 5G HetNet vsrsus the average MOS value of the users. This is again compared with the homogeneous networks. The 5G HetNet contain one MBS in addition with 4 various small cells along with various numbers of antennas. The results might be obtained by by setting up the value of N_c as $N_c = 0$. Then for obtaining the average MOS, the accumulated MOS for all the users is separated by K. Hence for obtaining the average MOS value, the 5G HetNet is made better than other homogeneous networks. The value of M = 10 or M-20 is made available by adding small cells or by removing the small cells for keeping the network lead upto about 12% to 28% which shows some certain improvement in the MOS consideration. Additionally, the MBS antenna increases from 10% to 80% for enhancing the average MOS value in the homogeneous networks and the heterogeneous networks. This could be limited for the values from 20% for 5G homogeneous networks and 6% for 5G heternogeneous networks. The employment of the small cells and the Macro cells in the whole network might leads to attract more users.Then the emergency in adding small cells will make the base stations to have more number of antennas. The fig indicates the same by increasing the SBS antenna numbers, thus improving the average MOS network.The final result indicates that the obtained fig is provided with a good averare value of MOS which could be obtained by setting the homogeneous MMaMIMO MBS and the heterogeneous 5G MMaMIMO MBS along with very less number of antennas held at the MBS.If the average MOS value is set up to about 5.4 might reached upto certain enhancement eitehr by setting N = 50 for homogeneous networks and N = 25 for heterogeneous networks along with some SBS.

The Fig. 5 illustrates the performance improvement identified in the proposed algorithm model when MOS value is set to 1 to 2. If the value of the MOS is set to 1, implies that there are no more constraints found in the optimization-based issues. Additionally, Fig. 5 also points out the MOS value of each individual user in the MMaMIMONetNet where the value of MBS is set up with 20 new antennas, along with the SBS which is made available with N = 1,2, and 3 renowned antennas. The first few users are accessible inside the tiny cell, based on the 10 users detected in the networks. Fig. 5 proves some robustness identified in the sizes of the web pages. In other words, the QoE value is considered by setting up the valuable constraints and the MOS value of each user is improved in consideration of that.

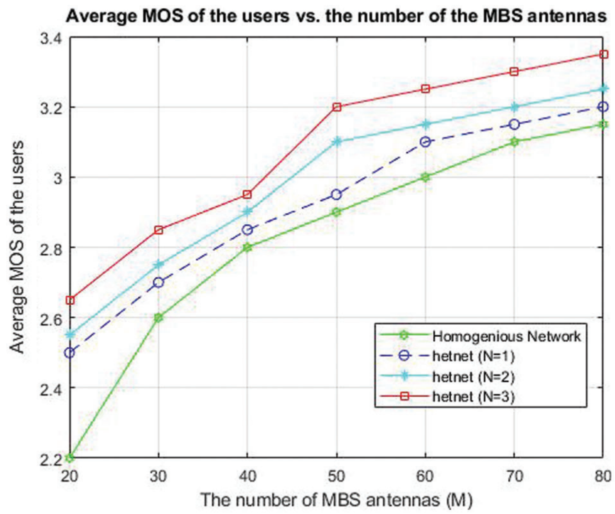

Figure 4: Number of MBS antennas *vs*. the Average MOS

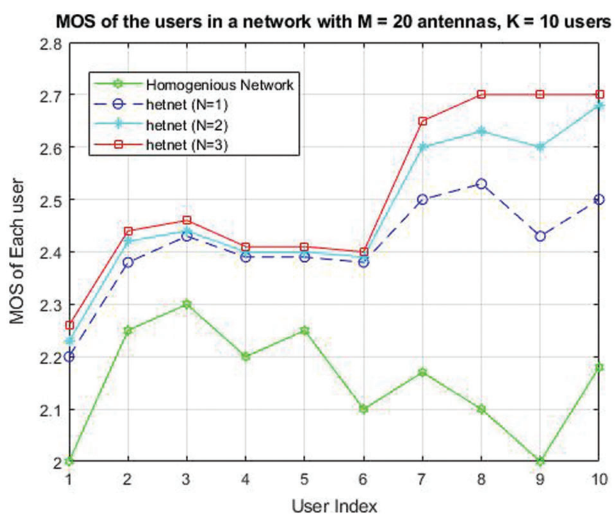

Figure 5: MOS of the users in a network with M = 20 antennas, K = 10 users

4.2 Video Services

In this work the video services are considered in addition with the internet related services. The network parameters which are considered similar might be considered as like the previous case. The considered parameters are designed by using the PSNR value that exists in between the 30 to 40 db. These parameters are x = 26.234, y = 0.054 and z = 4.564. The Fig. 6 illustrates the average MOS value in order to consider the MOS (video signals). The fig gives comparison about the average MOS of precoded homogeneous networks which contain one MBS along with the HetNet which in turn consists of one strong macro cell along with the 4 possible small cells in coordination with a wide variety of antennas.

Fig. 6 proves that based on the available number of antennas (MBS), the average value of HetNet is significantly upright than the available network which is homogeneous. The antenna numbers range might change from 20 to 80 and the average value of the MOS of heterogeneous networks is found to be 20% and homogeneous networks is found to be 30%. When the small cells or the MMaMIMO MBS are employed in the heterogeneous network that might lead to the enhanced condition of the user satisfaction. Then the requirement for the accumulation of the small cells might be processed smaller than the base station with more antenna numbers. From the fig it is very clear that the increase in the total number of heterogeneous antennas made available at the SBS will make the MOS value to get improved. The good average MOS is obtained from either the heterogeneous networks or the homogeneous networks with considerably a smaller number of heterogeneous antennas available at the MBS. The average value of MOS is approximated to N = 5 0 and N = 50 for homogeneous and heterogeneous networks respectively by considering one MBS and four SBS.

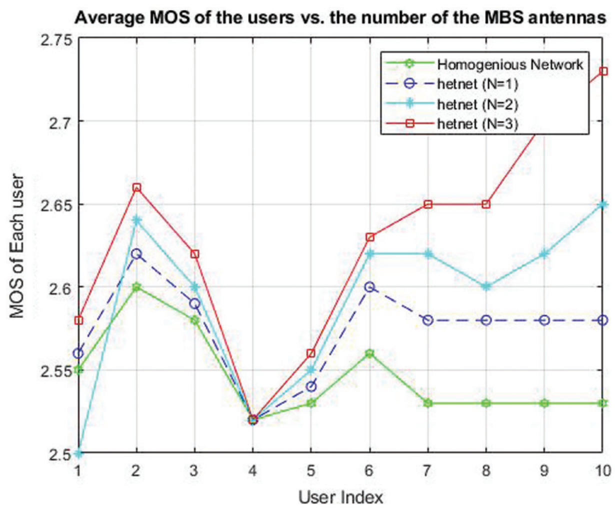

Figure 6: Average MOS of the user's *vs*. the number of MBS Antennas

4.3 Deep Learning Models

The suggested synchronized deep-learning based beamforming method is assessed in this part, and its potential to serve extremely maneuverable mmWave applications is demonstrated. The suggested deep learning method is then shown to be able to accurately predict beamforming orientations and approaching the ideal effective attainable rate. The effect of the system's primary networking and machine learning settings on effectiveness will investigate the most needed aspects of integrated communication and learning system which is suitable to adapt to the millimetre-wave environment and its sensitivity to synchronize the base station for showing its performance along with the untrained scenarios.

The FDCNN model is typically trained in order to predict the radiofrequency of the beamforming vector by considering the 512 + 512 selected beams for each base station. Normally the fuzzy-based deep convolutional neural network is used for coordinating the beamforming region which is trained by considering the dataset with size 20 k samples for achieving the better speed and the best antennas for base stations. The Fig. 7 given below is plotted between the effective achievable rate which is obtained from the proposed fuzzy-based deep Convolutional neural networks (FDCNN) which is trained for attaining the better beamforming solution under certain conditions like synchronization of the base stations in some cases and no synchronization at some other cases etc.

Finally, it is clear that the Fig. 7 illustrates that FDCNN model might be trained along with no available phase synchronization by fixing the separation at the other state of art methods in addition with the other deep learning algorithms which in turn requires the downlink phase synchronisation from considering the 4 possible SBS antennas by adding it with one MBS antenna. The line 1-4 denotes various SBS antennas. The possible conditions might be abandoned, if the available user (8 numbers) might be served as only one base station at the specified time. Here in this proposed model, the 4 possible base stations might coordinate together for training purposes, and from that one of the base stations is displayed to the user at the allocated point of time. From the overall analysis, it is quite clear that there exists a trade-off found in between the complexity of implementation and the identified performance of the system in consideration with the reliability and the data rate in these many systems for coordinated beamforming. An interesting future study path is to look into this trade-off for real systems.

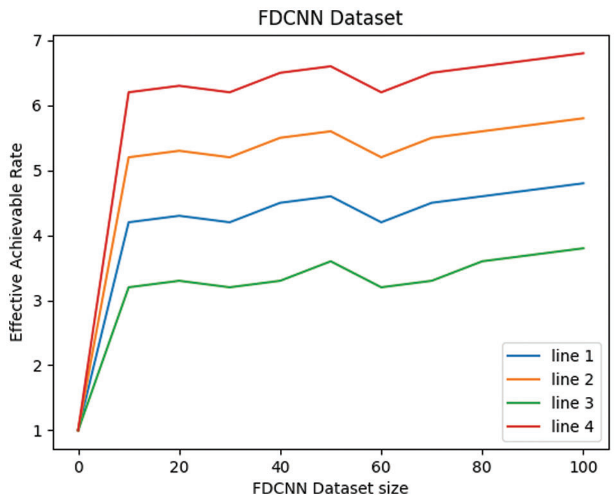

Figure 7: FDCNN dataset size *vs*. Effective achievable rates

5 Conclusion

The enhancement in the quality of experience faced by the user for for multimedia-related applications over the millimeter-wave band is investigated in this approach. The high attenuation loss in high frequencies is compensated with a massive array structure named MMaMIMO (Multiple-Input and Multiple-Output) HetNet(5G). The optimization problem which arises while maximizing the mean opinion score (MOS) is analyzed along with the QoE (Quality of Experience) metric by considering the base station (BS) powers in addition to the needed quality of service (QoS). The proposed work yields a better MoS and Quality of Service (QoS) and is proved in result analysis section. For solving the problems related to complexity and the dynamic nature might be resolved by using a deep reinforcement framework along with a fuzzy-based deep convolutional neural network (FDCNN) for extracting the features of highly correlated statistical information. The results obtained after experimentation proves that the method proposed might yield the highest satisfaction to the user by maximizing the antenna numbers and increasing the small-scale antennas at the base stations.

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