A Novel Approach to the Resource Allocation for the Cell Edge Users in 5G

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Abstract—In 5G network, resource allocation for the cell edge users is the major challenge. To address this challenge, we present GFDM (Generalized Frequency Division Multiplexing) for the physical layer of 5G wireless networks is a non orthogonal waveform with circularly pulse shaped mechanism. This mechanism is also used for resource allocation. In this paper, to allocate the weights on the filter bank of GFDM for cell edge users, an optimized Deep Neural Network (DNN) is presented in this paper. To enhance the performance of the DNN, weight parameters of it are optimized using Rain Optimization Algorithm (ROA). Using this proposed ROA based DNN, weight resources are allocated to the cell edge users optimally. Simulation results shows that the performance of the proposed resource allocation outperforms the conventional resource allocation in terms of normalized cell throughput.

Index Terms—GFDM, Resource allocation, optimization, deep neural network, rain optimization algorithm and cell throughput

I. Introduction

5G represents a significant update to mobile services across the consumers and the private & public sector. It promises improved bandwidth, reduced latency, and better handling of massive volumes of connected devices. In the 5G era, the need to guarantee Quality of Service (QoS) is based on the network slicing and optimizing the Network Functions (NF) placement more important than ever. The new generation of NF placement must handle cloud related operation and support dynamic placement at multiple location. The work of just duplicating resources across the board, to handle the increased potential load is not cost effective but not in a long way. Yet NF placement and optimization is a complex problem. The system need to enable dynamic connect [1]-[11].

A three phase approach is proposed in this paper to achieve NF placements- 1) Static Network, 2) Adaptive Network, & 3) Autonomous Network.

In the phase 1- static phase, the requirements for the new radio across multiple locations in the cell centre and edges have to own the public clouds, as the 5G mostly works with saving the data using internet/ cloud. Also ensuring the NF matching strategies are sound. The phase 1 mostly illustrates the physical layer of the 5G connection. This paper illustrates the different modulation techniques that could interpret the signal in a way other than OFDM which could help in better resource allocation and hence result in an improved QoS[12]-[15].

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In Phase 2- Adaptive Network phase, the NF creation is done at the end users. In this phase the network have to be dynamically provisioned and de-provisioned depending upon the network and load conditions. It is proven with the help of real time use cases like the User Equipments (UEs) moving in and out of the cell centre and the cell edge through the user edge platform [16], [17].

In the Phase 3- Autonomous Network phase, AI and ML are added to manage help NF placement and telemetry and Key Performance Indicator (KPI) from the early phases can be utilized in combination with Machine Learning platforms. AI driven prediction to improve resource allocation while lowering the cost [18]-[20].

This paper also exemplifies the phase-3 of 5G network connection using AI methodologies to interpret the signals.

The paper flow is as follows: Section II: Related works Section III: The existing candidates for waveform modulation techniques in 5G- A Comparison, Section IV: Adaptive allocation of resource, Section V: Optimizing the resource allocation using DNNs Section VI: Results, Section VII: Conclusion.

II. Related Works

In this section, some previous literatures which focused research on resource allocation for cell edge users are reviewed. In [21] the authors have presented enhanced resource allocation method to optimize the cell edge users' performance in LTE-A system. Using this proposed scheme, the authors have allocated index of Modulation and Coding Scheme, Radio Blocks and Carrier Components to the users optimally. In [22] the authors have formed cluster with center using the afnity propagation unsupervised learning. Then they have used the clusters for resource allocation. Besides, they have presented victim aware and coordination multipoint scheme to allocate the resource to the users in the cluster edge. In [23] the authors have proposed a dynamic fractional frequency reuse method to reduce the co-channel interference for cellular networks. The proposed method had two parts that are allocation of subcarrier and partition of frequency. In [24] the authors have presented resource allocation method based on clustering for dense femtocells. Using the proposed scheme, the authors have allocated appropriate channels to UEs at the dense femtocells.

In [25] the authors have presented an energy efficient resource allocation based on Stackelberg game for 5G cellular networks. The authors have solved the problem of assignment of sub-carrier in the process of optimization with the iteration algorithm. In [26] the authors have presented a resource allocation method based on a sealed bid single price auction model in 5G network. The proposed method has increased the throughput as well as it has reduced the resource block usage. In [27] the authors have presented dynamic small cell clustering and resource allocation based on weighted majority cooperative game in 5G green mobile network. Using the price value based proposed algorithm and utility function; small cells are allocated with the resources from the high majority small cells. In [28] the authors have presented resource allocation algorithm using fuzzy based adaptive priority and effective estimation of bandwidth. The proposed method attained the better QoS parameters.

III. The Existing Candidates for Waveform Modulation Techniques in 5G - A Comparison

The Multicarrier Modulation Technique, this is one of the most efficient techniques to divide the frequency spectrum into multiple subcarriers. It provides flexibility in a frequency selective multipath transmission.

The modulation technique used for current mobile communication is Orthogonal Frequency Division Multiplexing (OFDM). It is the most popular multi carrier method of modulation as it enables to produce high data rate signals with considerable complexity in the implementation and synchronization to MIMO. The two fundamental advantages of OFDM are its robustness against channel dispersion and its ease of phase and channel estimation in a time-varying environment. The usage of cyclic prefix (CP) combats ISI and intra-symbol interference, also to operate the signal in reliability. OFDM permits a flexible use of spectrum and also permits using different modulation schemes for different sub carriers. However, OFDM also has intrinsic disadvantages; it is very sensitive to the frequency and phase change, awfully high peak-to-average power ratio (PAPR), high out of band radiation. It requires frequency flat subcarriers and also prevents from reducing the latency by shortening the symbols. With all these it is the most suited mechanism for Multi-user MIMO.

Filter Bank Multiple Carrier (FBMC) is another contender for 5G NR introduced as early as in the 1960s. It is an evolved form of sub-band processing, harnessing the key features of original efficient sub-band processing based on the FFT and addressing some of the OFDM's shortcomings at the cost of increased implementation complexities. FBMC Multicarrier system, where data is broken into many orthogonal subcarrier streams. Multicarrier system based on filter banks at the transmitter and receiver. This technique does not require the CP extension and hence conserves BW. When compared to OFDM's large side lobes in frequency spectrum FDMA has smaller and sharper side lobes. At the receiver Multiple Access Interference (MAI) cancellation should be performed. MAI is suppressed due to the excellent frequency localization of the subcarriers in FBMC. FBMC is less flexible to synchronize with MIMO Degraded spectrum sensing performance due to the spectral leakage in OFDM signals High spectrum sensing resolution in FBMC.

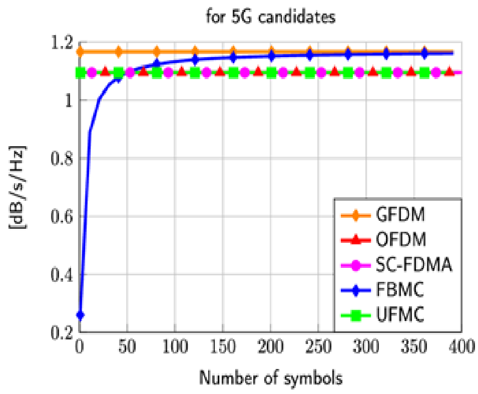

Fig. 1. Comparison of GFDM, OFDM, SC-FDMA, FBMC and UFMC [4]

Generalized Frequency Division Multiplexing (GFDM) proposed for the physical layer of 5G wireless networks is a non orthogonal waveform with circularly pulse shaped mechanism. This technique provides both frequency and time domains multi user scheduling. It is the most promising technique for 5G with a good amount of flexibility, mobility and resource allocation. All the algorithms that were generated for OFDM can be synchronized with GFDM. Also this scheme retains the characteristics of OFDM with additional implantation complexities. Though the waveforms are non-orthogonal the performance of GFDM can be improved compared to OFDM by inserting guard symbols and pinching the block boundaries. Also CP can be eliminated by the use of independent filters for each subcarrier. This provides better diversity and high spectral efficiency with lower latency.

Fig. 1 depicts the spectral efficiency versus the number of symbols in each modulation technique. It shows that FBMC and GFDM provide maximum performance. Table I depicts the comparison between the different modulation techniques discussed above. The Table I shows that the PAPR in GFDM when compared to OFDM, is low while keeping the spectral efficiency high. The table also depicts that the GFDM is less complex when compared to OFDM with respect to the integration with MIMO as well as Synchronization with 5G. Therefore GFDM forms the main interest for this paper.

IV. Adaptive Allocation of Resource

In a Multi user MIMO scenario the number of user equipments (UE) in cell edge and cell centre depends upon the mobility of the users. The cell edge users experience a low signal to noise ratio and signal to interference ratio. It is also due to low resource at the cell edges that the user equipments experience a lag in the connectivity to the available network. This paper proposes a novel approach to the resource allocation to the cell centre and cell edge users, cell edge users in particular as they move away from the BS. Increasing the BS power also might not be a feasible solution to improve the performance. The probable solution was proposed by us in as to introduce Physical Resource Blocks (PRBs) that behave like the BS and provide the required resource to the UE. The resource block needs to be carefully scheduled for providing service by using scheduling techniques. There are scheduling techniques that support the existing OFDM modulation technique. The scheduling techniques for the GFDM modulation technique and its adaptive resource allocation or performance is measured and illustrated here.

GFDM (Generalised Frequency Division Modulation) as introduced in the section 1 is one of the most popular modulation techniques for 5G. This techniques uses k subcarriers each circularly filtered and M symbols of data each. The total samples are kept at MK samples in circular filtering mechanism and the cyclic prefix and suffix can be added for frequency domain equalization at the receiver end. Also Rician fading can be introduced instead of AWGN to obtain an optimized resource allocation. The Fig. 2 depicts the system model for the proposed system.

TABLE I: COMPARISON OF PARAMETERS OF WAVEFORM TECHNIQUES

Parameters	OFDM	FBMC	GFDM
PAPR	HIGH	HIGH	LOW
Spectral efficiency	HIGH	LOW	HIGH
Cyclic Prefix	YES	NO	YES
Latency	SHORT	LONG	SHORT
Ease of integration with MIMO	YES	NO	YES
Synchronization requirement	HIGH	LOW	MEDIUM

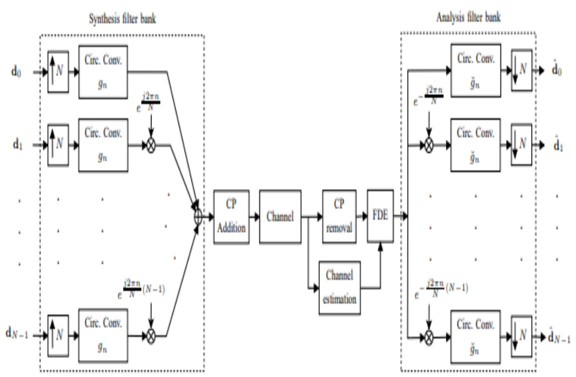

Fig. 2. System model of GFDM transceiver

It is defined by the following equations:

$$x[n] = \sum_{k=0}^{k-1} \sum_{m=0}^{m-1} d_{k,m} g_{k,m}[n], \qquad n = 0, \ldots., N-1 \tag{1}$$

where n denotes the sampling index, dk,m denotes the complex valued data sub symbol, taken from a QAM constellation, belonging to the kth subcarrier and mth sub-symbol and the gk,m[n] is the component of circularly filtered transmit filter represented as

$$g_{k,m}[n] = g\left[\left(n - Mk \right)_{\bmod N} \right] e^{j 2\pi \frac{kn}{k}} \tag{2}$$

It is shifted to mth sub symbol and is modulated to kth subcarrier.

$$g_{k,m} = \left[g_{k,m}[0], \ldots\ldots g_{k,m}[N-1] \right]^T \tag{3}$$

Equation (3) represents a collection of filter samples stored in gk,m which is further used as an input to the deep neural networks(DNNs) to optimize the resources to the UE to be connected to the network. The assignment or assumption below provides resource allocation to the UE when it is stationary.

Though the handoff or the mobility of the UEs could be seamless, the UE at the cell edge experiences a call drop or a disconnection to its network. In the case of a UE is mobile the resources can be allocated by making the process adaptive by adding weights, choice of the subcarrier available to be connected and keep the power levels high so as to reach the UE.

This assumption in Table II enables coherent reception, thus making the conventional achievable sum rate expression a reasonable performance measure.

SNR for user m on PRB n is calculated as

$$SNR_M^N = \left(\frac{P_{\max}}{N} \right) g_{j \to m}^n \, L\left(d^{\, j \to m} \right) * \frac{1}{N_0} \tag{4}$$

where, j is the serving cell of user m.

TABLE II: SOME ASSUMPTIONS FOR SIMULATION

Parameters	Value
Number of subcarriers K	128
Number of symbols M	5
Length of Cyclic Prefix NCP	32
Exponent of power delay profile Y	0.1
Number of channel taps NTAP	10
Number of transmit antennas	4
Number of Receive Antennas	4
Constellation Size Ω	4(QPSK)
Sub carrier spacing	15KHz
Bandwidth	1.5MHz

Fig. 3 depicts the dynamic weight allocation mechanism used before it is deep neural network.

The dynamic resource allocation to a UE can be calculated by the instantaneous SNR calculated using the weights on the filter banks denoted by wm. The weights allocated to the cell edge users are higher than at the cell centre. This allocation depends on the number of interfering channels at the cell edge. This weighting mechanism makes the system model adaptive and dynamically allocates the resource to the UE at the cell edge.

Sum rate maximization is taken care by using low-complexity algorithms, by successively allocating data streams to users in a greedy manner. Simulations have indicated that fewer than N streams should be used when M and K are small, and that spatial correlation makes it beneficial to divide the streams among many users. Hence the symbol error rate is also taken care.

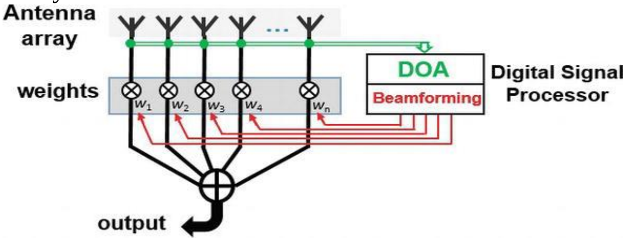

Fig. 3. Dynamic weight allocation mechanism

V. Optimizing the Resource Allocation using ROA Based DNN

The major concern in the 5G is to keep an account of the channel distribution and optimize the resource to the UE. The Fig. 3 depicts the architecture of fully connected deep neural network. It shows how the data is input and the controls we add for train the system to obtain the output desired. The architecture consists of prescribed number of layers L each of which consisting of a linear operation followed by a point-wise nonlinearity also known as an activation function σ. It is adaptive which means, the trained system learns the next possible output by using predictive algorithms. The learning goals depend on the weights W1….WL used in the previous stage. (See Fig. 4)

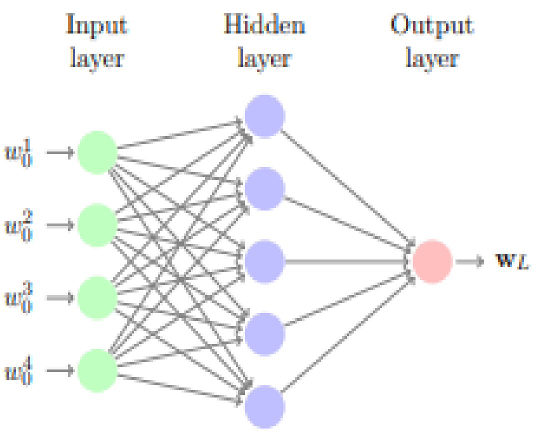

Fig. 4. Fully connected deep neural network

The step by step process of DNN as follows:

Step 1: Read the number of n input nodes for input layer. The number of input node is same as the number of selected features.

Step 2: Assign the number of layers in the hidden layer that need to be trained with data. The input layer and hidden layer connected with the help of weight value which represented as wt_{ij}^{H} . Similarly, the weight between hidden layer and output layer is represented as wt_{ij}^{O} .

Step 3: Then, initialize the bias and learning rate values for each node and the weight will be selected arbitrarily in forwarding propagation initially.

Step 4: Also, define the number of epochs to make the values of the back propagation from the output to the input direction.

Step 5: Then, in the first hidden layer, the weighted values of input are fed to the summing function with the bias of the neuron as in equation (16).

$$C_{H\_1}(i=1,2..,K)=\left(\sum_{m=1}^{M} wt_{ij}^{h} R_m\right)+b_x \tag{5}$$

where b_x constant value acts as bias, wt_{ij}^{h} is the interconnection weight between the input and hidden layer M and K representing the number of input and hidden nodes in the first hidden layer.

Step 6: Then, the activation function is applied to the output of the first hidden layer is given as,

$$F\left(C_{H\_1}(i)\right)=\frac{1}{\left(1+e^{-C_{H\_1}(i)}\right)} \tag{6}$$

where, $F(\cdot)$ is the sigmoid activation function.

Step 7: Similarly, the operation of nth hidden layer output is calculated as follows;

$$C_{H\_n}(i)=\left(\sum_{z=1}^{K} wt_{ij}^{o} F\left(C_{H\_(n-1)}(z)\right)\right)+b_p \tag{7}$$

where, b_p is the bias of p^{th} the hidden node, wt_{ij} is the interconnection weight between the $(n-1)^{th}$ hidden layer and $(n)^{th}$ hidden layer with K hidden nodes.

The activation function which is the output of the n^{th} hidden layer is given as,

$$F\left(C_{H\_n}(i)\right)=\frac{1}{\left(1+e^{-C_{H\_n}(i)}\right)} \tag{8}$$

Step 8: At the output layer, the output of n^{th} the hidden layer is again multiplied with the interconnection weights (i.e. weight between the n^{th} hidden layer and output layer) and then summed up with the bias (b_q) as

$$C(k)=F\left(\sum_{j=1}^{K} wt_{jk}^{O}\ f\left(C_{H\_y}(j)\right)+b_q\right) \tag{9}$$

where wt_{jk} represents the interconnection weight at the n^{th} hidden layer and output layer having j^{th} and k^{th} nodes respectively. The activation function at the output layer acts as the output of the whole model.

Step 9: After the output calculation, the network error is calculated. The error calculation is given in equation (10).

$$Error(m) = \frac{1}{M}\sum_{m=1}^{M}\left(Actual(C_m) - T\arg et(C_m)\right)^2 \quad (10)$$

where, $T\arg et(C_m)$ is the estimated network output and $Actual(C_m)$ is the actual output. The error must be minimized for getting optimal network structure. Hence, the weight values must be adjusted until the error gets decreased at every iteration. However, to enhance the performance of the DNN, the weight parameters (wt) between the layers are to be selected optimally. So, for optimal weight selection ROA algorithm is presented in this paper.

Weight selection using ROA algorithm

The rain optimization algorithm (ROA) imitates the behaviour of rain drops. The process for selecting optimal weight parameters using ROA algorithm is described as follows:

Initialization: In this algorithm, each particle or raindrop in a population denotes the solution. Solution of this approach is optimal weight parameters. The initialization of ith drop is defined as follows,

$$D^i = \{y_{i,1}, y_{i,2}, y_{i,3,.....}, y_{i,j}\} i \in [1,2,3,.....,s] \quad (11)$$

where, s denotes the size of the population, j denotes the number of optimization variables and $y_{i,j}$ denotes the variables of optimization problem. For this work, the variable can be defined as follows,

$$y_{i,j} = \{wt\}_{i,j} \quad (12)$$

Rainfall manages raindrops during the process of optimization. It is created by uniform random distribution function and subject to every one of the constraints in Equation (12).

$$y_{i,j} = U(up_j, low_j) \quad (13)$$

where, U denotes the uniform distribution function, upj and lowj denote the upper and lower limits of yj.

Fitness calculation: For each initialized solution, fitness or objective function is calculated to evaluate the solution. To select the optimal weight parameters, the solution is to be evaluated with the following fitness function,

$$Fit_i = Min(Error\ (m)) \quad (14)$$

Update the solution: As the raindrop (D) is defined as a point in N dimensional space, the domain which has the radius vector (r) places around the point is known as the neighbourhood. The neighbourhood can be updated when the changes occur in the value of raindrop.

During the process of optimization, a point in the neighbourhood of drop can be generated randomly. The ith drop's neighbourhood point q is denoted as NPqi. Using the following condition, neighbour point of the drop is generated.

$$\left\|\hat{u}_p * \left(D^i - NP_q^i\right)\right\| \le \left\|\hat{u}_p * r\right\| \quad for \quad \begin{array}{l} i = 1,2,3,....,s \\ q = 1,2,3,.....,np \\ p = 1,2,3,.....,z \end{array} \quad (15)$$

where, np denotes the number of neighbour points, $\hat{u}_p$ denotes the unit vector of the pth dimension. r denotes the size of the neighbourhood in terms of real positive vector and can be defined as follows,

$$r = f(itr) * r_{initial} \quad (16)$$

where, rinitial denotes the initial size of the neighbourhood and f(itr) denoted as a function used to adapt the size of the neighbourhood within iterations.

Dominant drop: The dominant neighbour point (NP_d^i) is one of the point chosen from the drop's (Di) neighbour point. It should satisfy the following condition,

$$Fit(D^i) > Fit(NP_d^i)$$
$$Fit(NP_q^i) > Fit(NP_d^i)$$

Active drop: The drop is considered as active drop if it has dominant neighbour point.

Inactive drop: the drop is considered as inactive drop if it doesn't have dominant neighbour point.

Process of explosion: If the drop has no sufficient neighbour points or it couldn't continue the search process to attain the optimal minimum, the explosion process is initiated to solve this condition of the drop. Using equation (17), the number of neighbour points can be created in this explosion process.

$$np_E = be \times np \times ce \quad (17)$$

where, npE denotes the number of neighbour points created in the process of explosion, np denotes the number of neighbour points without the process of explosion and ce denotes the counter of explosion.

Rank of raindrop: For each rain drop, rank (R) is calculated using () in every iteration. This rank is used in the merit order list.

$$V1_t^i = Fit(D^i)\Big|_{at\, t^{th} iteration} - Fit(D^i)\Big|_{at\, first iteration} \quad (18)$$

$$V2_t^i = Fit\left(D^i\right)\Big|_{att^{th}iteration} \quad (19)$$

$$R_t^i = order\left(V1_t^i\right) * \phi_1 + order\left(V2_t^i\right) * \phi_2 \quad (20)$$

where, $V1_t^i$ denotes the difference between the fitness function of drop Di at first iteration and tth iteration, $V2_t^i$ denotes the fitness function of drop Di at tth iteration, $order\left(V1_t^i\right)$ and $order\left(V2_t^i\right)$ denote the orders of V1 and V2 at tth iteration when they are arranged in the form of ascending order, ϕ_1 and ϕ_2 denote the weighting coefficients that are assumed as 0.5 and R_t^i denotes the rank of rain drop at tth iteration.

List of merit order: For every iteration, ranks of the rain drops are arranged in ascending order. From the list, each low ranking drop can be removed and some drops can be given significant rights. The drop with minimum fitness function is considered as the optimal solution or map function.

Termination: The above process is repeated until finding the solution with the minimum fitness function. Otherwise, the algorithm is terminated.

Resource allocation

For a parameterized resource allocation the policy Φ (h, θ) can be defined for a L layer DNN as,

$$\phi(h,\theta) = \sigma_L\left(W_L\left(\sigma_{L-1}\left(W_L\left(\ldots\ldots\left(\sigma_1\left(W_1 h\right)\right)\right)\right)\right)\right) \quad (21)$$

Further the experiments on the use of DNN in maximizing capacity over the more complex problem of allocating power over an interference channel. We first consider the problem of m transmitters communicating with a common receiver, or base station. When the fading channels defined by $h = \left[h^1, h^2, \ldots\ldots h^m\right]$, the channel capacity then is determined by the SINR (Signal to noise plus interference ratio) given by

$$SINR^i = \frac{h^i p^i(h)}{\left(v^i + \sum_{j \neq 1} h^i p^i(h)\right)} \quad (22)$$

This result in a capacity function which is observed by user I is expressed as

$$f^i\left(p^i(h), h\right) = \frac{\log\left(1 + h^{ij} p^i(h)\right)}{\left(v^i + \sum_{j \neq 1} h^i p^i(h)\right)} \quad (23)$$

This results in this architecture denoting all channel states of h which for the input to the MIMO Network having two hidden layers of sizes 32 and 16 respectively. The outputs of the DNN depict μi and with the standard deviations σi for all the values of i truncated Gaussian distributions. This network is tested for performance and computational complexity. (See Fig. 5)

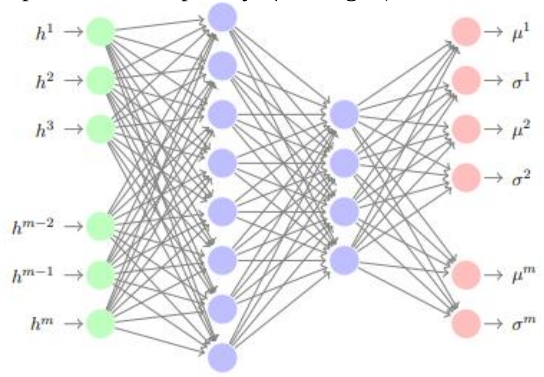

Fig. 5. New architecture of DNN for resource allocation in MU- MIMO

VI. Results and Discussion

The proposed system is simulated using MATLAB. Table II shows the simulation parameters and its values. As shown in the table, in this simulation, 19 cells are considered. Each cell has varied 20, 40 and 80 users. Bandwidth of the system is 20MHz and bandwidth of the subcarrier is 15KHz. Radius of each cell is 250m and carrier frequency is 2000MHz. Transmit power of BS is 46dBm and Noise power spectral density is -174dBm/Hz. (See Table III)

The Number of users at the cell edge is specified. The probable degree of freedom is also specified. The using space time block coding technique the beam formed output is depicted for the degree of freedom. The major lobe depicts the location of the subarray and the direction of maximum power. The side lobes depict the interfering signals from other users at the cell edge either connected to the same subarray or any nearby subarray. Fig. 6 and Fig. 7 shows the direction of arrival detection for 3 transmitting antenna and 10 receiving antenna and 3 transmitting antenna and 15 receiving antenna are respectively used. Receiving antenna is considered as the user equipment and here the uplink communication takes place. A smart dual beam is used to transmit the same signal in all directions from the Trans receiver of the user towards the subarray. Depending on the distance and the polarization of the signals they serve the UE. It is evident that as the degree of freedom increases the Bit Error Rate decreases and SINR increases. It is an optimized output when compared to only using the subarray with beamforming.

TABLE III: SIMULATOR PARAMETER AND ITS VALUES

Parameter	Value
Network size	19 cells
Users per cell	20, 40, 80
System bandwidth	20 MHz
Subcarriers	1200
Subcarrier's bandwidth	15KHz
Cell radius	250 m
Carrier frequency	2000MHz
BS Transmit power	46dBm
Noise power spectral density	-174dBm/Hz

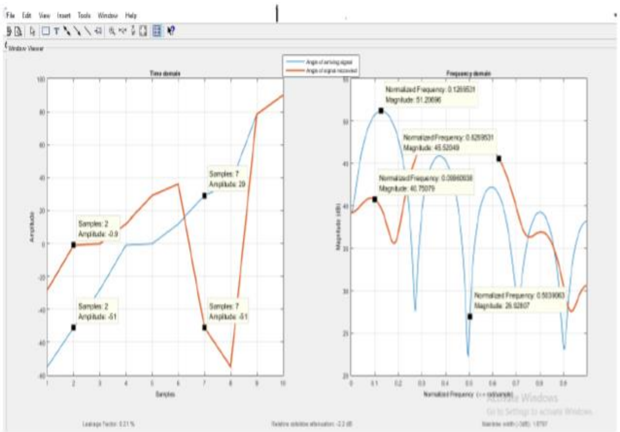

Fig. 6. DOA estimation for 10Rx antenna

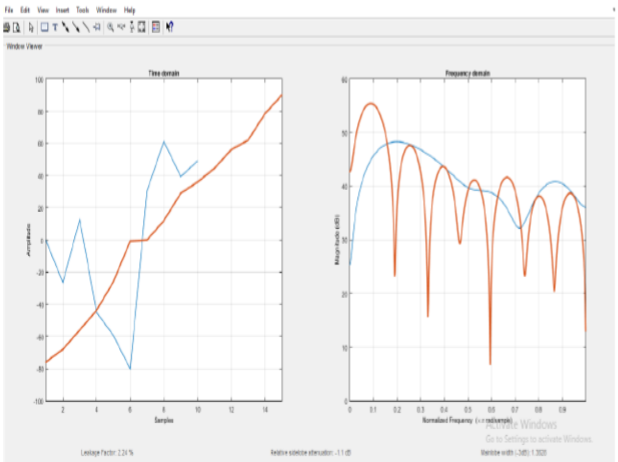

Fig. 7. DOA estimation for 3Tx and 15Rx antenna

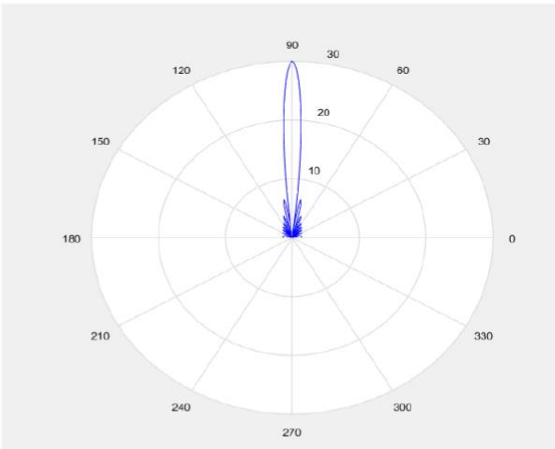

Fig. 8. Beamforming for 20 User and 10° of freedom

The Blue line in the Fig. 6 & Fig. 7 indicates the angle of arrival of the signals from the PRB and orange line indicates the angle of signal arrived at the receiver end of the antenna. Then the information received in the receiving antenna and the information at the transmitter end is compared to calculate the leakage factor. The number of cells is assumed to be 19 for simulation purposes. Fig. 8 and Fig. 9 shows the beam formation for the 20 users and 15 users respectively and the degree of freedom is specified and signal edge is also specified. It is observed that the as the number of UEs increases the weights of the filters change adaptively to optimize the resource allocation to the UE and keep it connected to the Network. A narrow beam is formed as w r t increase in the distance between the UE and the PRB.

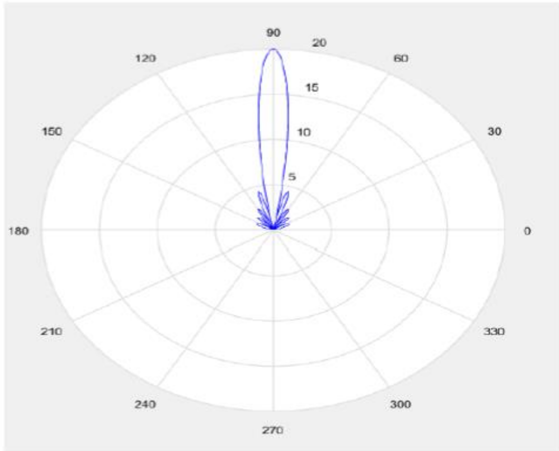

Fig. 9. Beamforming for 15 User and 5° of freedom

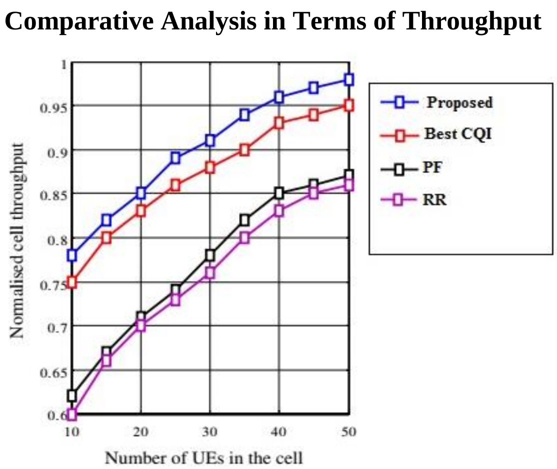

Fig. 10. Normalized cell throughput under random deployment

In this section, the performance of the proposed resource allocation is evaluated in terms of normalized cell throughput. Besides, the performance of the proposed scheme is compared with that of the conventional resource allocation techniques such as Best Channel Quality Indicator (Best CQI), Round Robin (RR) and Proportionate Fair (PF). Fig. 10 shows the comparative analysis of the normalized cell throughput of the different resource allocation schemes for varying number of UE in the cell under the condition of random deployment. As shown in the figure, cell throughput is increased when the number of UE in the cell increases. Besides, compared to conventional resource allocation schemes Best CQI, PF and RR, the cell throughput of the proposed resource allocation scheme is increased to 4%, 17% and 20% respectively. The comparative analysis of the normalized cell throughput of the different resource allocation schemes for varying number of UE in the cell under the condition of cell-centre deployment is shown in Fig. 11. As shown in the figure, cell throughput of the proposed resource allocation scheme increases to 3%, 12% and 15% than that of the Best CQI, PF and RR respectively. Fig. 12 shows the comparative analysis of the normalized cell throughput of the different resource allocation schemes for varying number of UE in the cell under the condition of cell-edge deployment. As depicted in the figure, compared to Best CQI, PF and RR, cell throughput of the proposed resource allocation scheme is increased to 1.3%, 31% and 34% respectively.

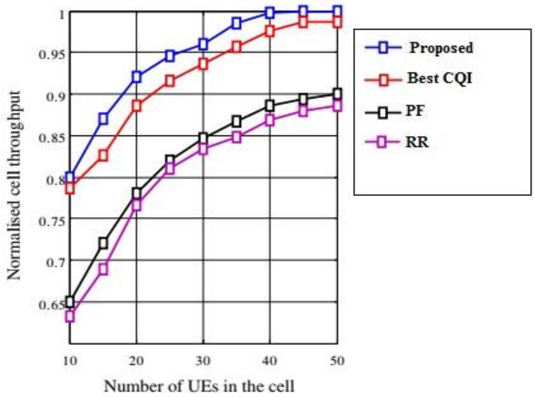

Fig. 11. Normalized cell throughput under cell-centre deployment

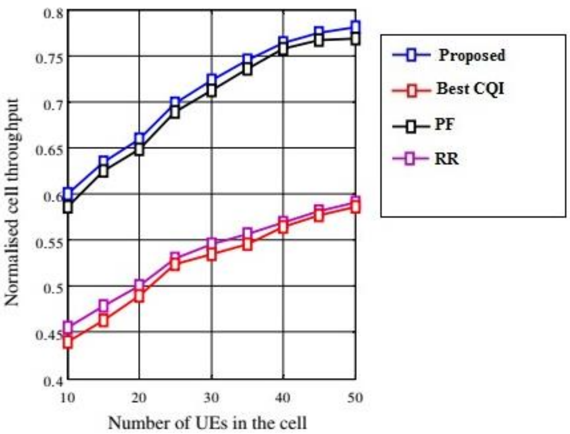

Fig. 12. Normalized cell throughput under cell-edge deployment

VII. Conclusion

The multiuser MIMO network is classified into 3 and they are analyzed for the density of user equipments and resource allocation to the user equipments. In this paper,the modulation technique GFDM is shown to be more efficient than OFDM modulation technique w.r.t better performance in the MU MIMO system. This is applied to the UE in the cell edge for a better resource allocation using adaptive weights depending upon the distance of the UE to the PRB. Usage of PRB might increase the hardware requirement to continue the UE in the network in 5G, but the computational complexity is reduced by using a learning network. Deep neural network is used to optimize the resource allocation to the UE in the Cell edge and the beamforming shows a narrower main lobe toward the UE with lesser side bands. Also the Figure shows the comparative analysis of the normalized cell throughput of the different resource allocation schemes for varying number of UE in the cell under the condition of cell-edge deployment. The cell throughput of the proposed resource allocation scheme is increased to 1.3%, 31% and 34% respectively. Hence it is observed that the proposed system is a better resource allocation technique.

Conflict of Interest

The authors declare no conflict of interest.

The most important of the papers are referred to bring out the results hence are indexed towards the end.

Contribution of Authors

The manuscript presented is a research work of the 1st author Anitha S Sastry. The second author suggested the methodology and finally, the work was approved by all the authors.

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