An Energy Efficient Resource Allocation and Transmit Antenna Selection Scheme in mm-Wave Using Massive MIMO Technology

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Research Article

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Posted Date: June 29th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-594206/v1

An energy efficient resource allocation and transmit antenna selection scheme in mm-wave using massive MIMO technology

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Abstract: The massive Multiple-Input Multiple-Output (MIMO) improves the reliability of transmission and capacity of the channel. Resource allocation (RA) and Transmit Antenna Selection (TAS) can minimize the complexity in implementation and hardware costs. In this research, both the RA as well as the TAS of wireless communication in millimetre- wave (mm-wave) with massive MIMO technology is considered. Two different solutions are developed for this research such as the Deep Learning method for efficient resource allocation process and optimization algorithm for Transmit Antenna Selection (TAS) process. Here, the RA process is done with the help of Attention Based Capsule Auto-Encoder (ACAE) architecture which allocates the radio resources like power, space, time and frequency to all the available users in the system. Further, Battle Royale Optimization (BRO) algorithm is utilized to select an efficient antenna from multiple antennas at BS. This optimization algorithm optimally selects an efficient antenna so that, user equipments (UEs) can create high quality links and achieves a reduced power consumption rate of the whole architecture. The overall system performance depends on the selection of optimal antenna which in terms enhances Spectral Efficiency (SE), Energy Efficiency (EE), reliability, and diversity gain of MIMO technology. In this way, both RA and optimal antenna selection schemes are performed to maximize the overall performance of wireless communication with massive MIMO technology for 5G wireless communication applications. The implementation of the proposed methodology is evaluated on MATLAB. Finally, the efficiency of the developed method is improved with respect to the capacity, EE and SE.

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1. Introduction

Wireless communication has been enhanced by developing new techniques in the last few years. The extension model of MIMO is the Massive which exploits multi-antenna to provide throughput and for improving the system efficiency [1]. In the fifth-generation (5G) networks, massive MIMO is considered as a primary method for gaining a large achievement in energy and spectral efficiencies. [2]. For the fifth-generation wireless communication systems, mm-wave technology is considered as a promising solution because of its huge available spectrum ranging from 30 GHz to 300 GHz [3]. Moreover, hybridization of mm-wave with massive MIMO is considered as another prominent 5G wireless communication technology which mainly intended to achieve unprecedented energy efficiency (EE) gains [4]. When compared to single antenna systems, a massive MIMO system can improve EE by three orders of magnitude. In massive MIMO, the energy-efficient design is a hot topic that considers different

techniques to enhance the system performance with Transmit Antenna Selection (TAS) [5] and Resource Allocation (RA) [6] strategy.

The RA in which 5G users require different resources to operate effectively with the unavailability of resources [11]. RA is a multi-objective optimization issue that considers the capacity of the channel, constraints in QoS and the transmitted power. Different kinds of studies had been developed in the previous years to effectively exploit the available spectrum resources with desired quality of service (QoS) [12], lower path loss, reduced battery consumption, increased EE [13] and SE [14] are obtained by executing the wireless communication networks that designed with a small distance between their terminals. The user's Quality 0f Experience (QoE) has been enhanced with this RA process [15]. Moreover, RA issues are handled with the help of some parameters like data rate, EE, SE, QoS, fairness and so on. The dynamic RA process enhances the efficiency of spectrums and establishes spatial multiplexing with directional data transmission process [16]. So, an efficient method is necessary to provide better services to users in the 5G wireless communication network. In addition, 5G needs high throughput with improved reliability and less latency [17]. TAS scheme is considered as one of the basic strategies in MIMO systems that enhance the efficiency of transceiver antenna with high data rate and system capacity. MIMO system achieves good spatial diversity by establishing several antennas at the transmitter/receiver [7].

Even though it achieves transmission reliability and higher multiplexing gain to enhance system capacity and data rate, it is considerably affected by some factors [8]. Hardware complexity and price becomes significant factors because antennas are equipped with a separate RF chain that contains exclusive RF components like filters, amplifiers, ADC/DAC, and up-/down-converters etc [9]. So, the antenna selection mechanism is considered as the promising solution that adopts available subset antennas at the transmitter and receiver sides. This helps to minimize the RF chains to the similar size of selected antennas in order to develop the implementation MIMO systems more realistic. Hence, the antenna selection method has attracted the interest of researchers [10]. Different methods like global optimal searching, bound searching and bidirectional branch were developed for TAS. But a major drawback of using TAS is a complication and high cost because of different RF chains. Hence, it is very essential to consider both TAS and RA process in a mm-wave massive MIMO system. Recently many TAS and RA approaches were utilized for MIMO [18] [19] [20].

1.1 Motivation

In massive MIMO technology, a base station (BS) in a wireless communication network is furnished with multiple numbers of antennas to enable communication between multi-users concurrently with the same frequency resources. Because of its ability to enhance sum data rate, EE and SE, it is considered as one of the main technology in 5G communications. So, wireless communication under laid with mm-wave massive MIMO technology is considered as one of the main research topics. This technology can provide maximum SE as well as a maximum signal-to-interference-plus-noise ratio (SINR) to the wireless communication network. Anyhow, selection of transmit antenna from multiple antennas is regarded as a necessary issue in 5G communication and it requires an effective way to enhance the spatial modulation (SM) systems. For the large-scale MIMO design, the TAS computational complexity in large scale SM is very high which degrades the applications of TAS in large MIMO design.

Conversely, resource allocation between users and mobile station in wireless communication with MIMO technology is considered as another issue. This requires strong mutual connection between the users and mobile stations for increasing the system performance. But, to provide the resources to multi-users with RA is considered as a challenging task. Due to the aforementioned challenges, it is very important to achieve the high

EE, SE and capacity without increasing the rate of the power consumption. So, this motivates us to develop a novel technique in joint TAS and RA process in wireless communication network with mm-wave massive MIMO technology. As a result, the SE and EE can be enhanced by the high data requirement that can be fulfilled by the dynamic RA strategy as well the antenna selection process.

1.2 Contribution

The contribution of this research is listed as follows:

- To overcome from complexity in implementation and hardware costs, RA and TAS is developed. Here the RA is done by ACAE method and the TAS is done by BRO optimization.
- RA allocates the radio resources like power, space, time and frequency to all the available users in the system.
- To develop a TAS in a massive MIMO system to enhance the capacity, Energy Efficiency (EE) as well Spectral Efficiency (SE) of wireless communication.
- Both RA and optimal antenna selection schemes are performed to maximize the overall performance of the system.
- Different kinds of performance parameters are utilized to evaluate both techniques used in RA as well as antenna selection scheme in massive MIMO system and it is compared with recently developed papers.

The remaining structure of the article is arranged as: section 2 gives the recent related research works; section 3 explained the proposed scheme; section 4 gives the discussion of implemented results and finally, section 5 gives the overall conclusion of the research paper.

2. Related works

Salman Khalid *et al.* [21] have developed a probabilistic distribution learning method that used Exhaustive Search algorithm for optimal TAS process and successive interference cancellation for proceeding. This method provides a better solution using an increased number of samples. Anyhow, this method was not feasible for the selection of antennas due to the massive growth computational complexity with an increasing amount of antennas. For the real-time antenna selection, this method was considered as the efficient and optimum solution.

Nguyen *et al.* [22] have suggested a Point to point bidirectional Full Duplex (FD) Spatial Modulating (SM) MIMO system was utilized to obtain more channel gain with TAS scheme based on successive interference cancellation and analytical solution. For the FD-SM-MIMO system with TAS, this paper derives closed-form expressions of the outage probability (OP) and the symbol error probability (SEP).

Kim [23] has developed an efficient TAS for Receive Spatial Modulation (RSM) on the basis of MIMO; this article developed two efficient TAS selection process. From the available number of N_T transmit antennas, N_S transmit antennas were selected with the help of the TAS selection method on the basis of the maximization of received SNR. After that, the modified TAS selection method achieves two subsequent selection phases to minimize complexity. Active transmit antennas were selected in the pre-processing step and remaining active antennas were selected in the post-processing phase. Moreover, the complexity of the system is significantly minimized by the simple norm-based algorithm.

Olyaee *et al.* [24] have implemented a MIMO with Zero- Forcing (ZF) method. This approach aimed to increase the EE on the basis of the joint antenna and the user selection algorithm was exploited for MIMO with ZF. The main advantage of the proposed method was it found the cardinality of the antenna subset, user subset and indices. The Semi-orthogonal User Selection (SUS) algorithm was used to select the optimum number of antennas. But when correlation increased, EE will get minimized.

Hao *et al.* [25] have designed proceeding for Macro Users (MUs) and Small cell Base stations (SBSs) with several structures. Then, the subchannel and joint power were utilized to maximize the EE with a wireless backhaul link. To overcome the non-convexity issue Difference of Convex Programming (DCP) was designed. Further a two-loop iterative was developed to achieve subchannel and power. The experimental results attain an enhanced EE due to the less energy consumption.

2.1 Problem Statement

The algorithm [21] learns from the probability distribution of the best possible solutions. For the real time antenna selection, this method was considered as the efficient and optimum solution. Anyhow, this method was not feasible for the selection of antennas due to the massive growth computational complexity with an increasing amount of antennas. The methods FD-SM-MIMO [22] analyze the performance by imperfect successive interference cancellation and analytical solution. But when the transmission power is large, the TAS of this method has become worst. The method [23] provides higher Bit Error Rate (BER) and the better tradeoff between the parameter but it suffers from the high computational complexity. The ZF method [24] provides better EE and capacity on the basis of the joint antenna and the user selection algorithm was exploited for MIMO with ZF. But when correlation increased, EE will get minimized. The method [25] provides high EE and throughput due to its low energy consumption. But the implementation of this method was high with respect to the system size.

3. Proposed methodology

This section explains the resource allocation process, system model, antenna selection by the optimization algorithm, Fitness function generation, computational complexity and the application of the massive MIMO of the 5G network.

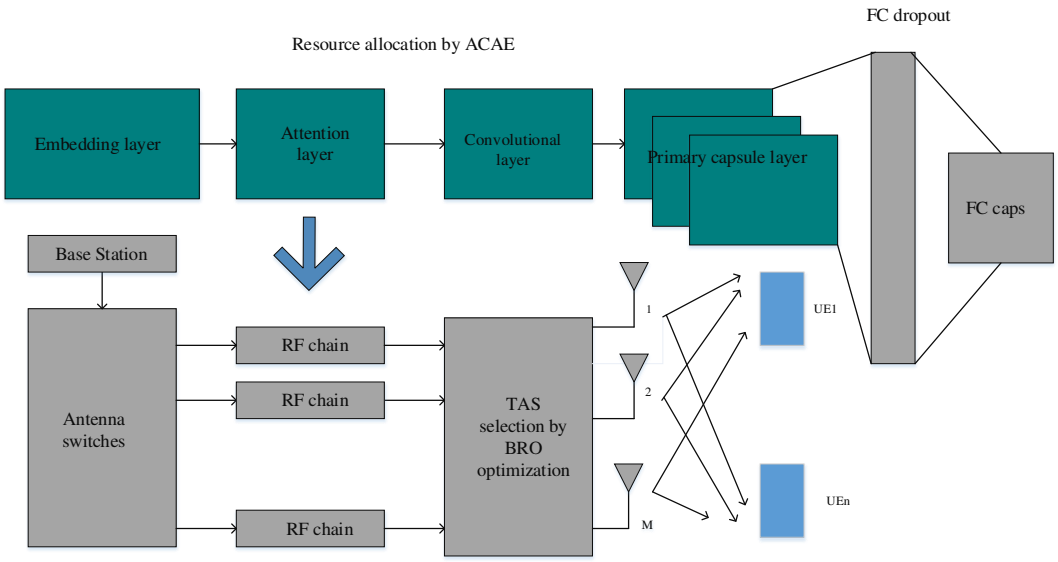


Figure 1: Architecture of the proposed work

Figure 1 represents the architecture of the proposed work. The structure of the ACAE consists of an embedded, fully connected capsule layer, convolution, attention, and primary capsule layer. The embedding layer is used for converting the input into low dimensional embedding. The attention layer used to select a subset which depends on the weights of attention. The convolutional layer is used for extracting the features of the input sequence at various positions by the convolution operation and these results are given to the primary

capsule for producing the vector structures. At last, the fully connected capsule layer produces the resource allocation results through the dynamic routing method on the basis of the result obtained from the primary capsule layer. Further, mm-wave BS has N number of RF chain and M antennas which provides $K(K \le N \le M)$ single antenna user at the same time frequency. During the process of communication, BS has perfect CSI. In addition, the large number of RF in both UE and BS takes more power due to filters, amplifiers, and ADC/DAC.

3.1 Resource allocation by ACAE

Different user require a different amounts of resources. Depending on the users' need, the resource is allocated by resource allocation scheme. To improve the QoS and maximization of EE, the deep learning-based Attention Based Capsule Auto-Encoder is developed which allocate the radio resources like power, space, time and frequency higher transmission data rate and throughput. This deep learning is employed to provide less consumption of energy, high SE, and EE. Thereby guarantees the fast, soft and massive 5G networks in mm-wave.

The Capsule Network (CN) can indicate the possibility that some feature remains by its length. The features spatial information can also be represented by each capsule vectors dimension. Thus, the CN can learn several identical feature variants, which show the spatial association among features. In addition a squash function as the nonlinear activation function is developed for classifying various capsules more easily. It comprises of a decoder, and an encoder. An encoder has a convolutional layer, PrimaryCaps layer, and a DigitCaps layer; the decoder has 3 fully-connected layers. The convolutional layer has a traditional convolution operation and extracts the input feature map input data through the ReLU layer. In PrimaryCaps layer by using linear combination this layer divides the overall feature maps into capsules, which covers a reshape operation and convolution layer. Then the all maps are classified into groups based capsules by reshaping. In digitcaps layer, the relationships between several hierarchy capsule layers are created. The dynamic routed algorithm and squash method are fed on the capsules layers for weight updating. The output capsule vectors have the dimension through the conversion of matrix from the primary caps are given to two branches: first branch is used for computing the capsule length and the second branch is used to reconstruct the input feature maps via decoding.

Here the capsule network is integrated with an attention mechanism to provide the better resource allocation. In this work, ACAE [26] is utilized for resource allocation due to its less energy consumption. The attention mechanism is included in the capsule network. The attention layer is utilized after the convolutional, the attention mechanism will assign various weights to every feature produced by the convolutional layer.

Embedding layer

The embedding layer is used to converts the input into low dimensional embedding. Let $R=[X_1, X_2, ...X_m]$ is the input of the resource with m length in the resource R. Resource embedding E_i is expressed as

$$E_i = V\beta_i \tag{1}$$

Where β_i is the output of the ith capsule and V is the parameter to be learned.

Attention layer

The attention layer ensures various weights when it is used before the convolutional layer; further, if the convolutional layer is utilized after the attention mechanism will assign various weights to every feature produced by the convolutional layer. When the convolutional layer is assigned before the attention mechanism, the resource allocation will lost. Therefore the attention layer is used before the convolutional layer. For the threshold value η, the aim of the attention layer is select the RA, where the threshold value is less than the attention value.

$K = \{K_{1,...} K_n\} \in S^n$ is the attention value, the matrix of the parameter is $m \in S^{u \times de}$ u is a attention window, If u is an even number then,

$$K_i = f(m \circ E_{i-u/2:i+u/2} + b) \tag{2}$$

If u is an odd number then,

$$K_i = f(m \circ E_{i-u-1/2:i+u/2} + b) \tag{3}$$

Where f is a non-linear function, $\circ$ is a multiplication element and bias is represented as b. The edge points are satisfied using zero-padding. After achieving the attention values for resource allocation, compare it to the threshold value η.

$$\hat{E}_i = \begin{cases} E_i & k_i > \eta \\ 0 & k_i \le \eta \end{cases} \quad 1 \le i \le n \tag{4}$$

Convolution layer

It is a regular convolutional layer which is used for extracting the input features at various positions by a convolution operation. In the convolution layer, each neuron is linked to an upper layer by a set of weights. Then the sum of these local weights is given to a non-linear activate function for producing the final result of all neurons in the convolutional layer.

Let m_i is the feature map of the ith convolutional layer. Then m_i is calculated a

$$m_i = f_{conv}(E_{i:i+c-1} \otimes w_i + d_i) \in R^{n-c+1} \tag{5}$$

where $w_i \in R^{c \times de}$ is the ith filter, $e_{i:i+c-1}$ is the concatenated layer, $\otimes$ is the kernel function and d_i is the bias vector, c is the size of filter and de is dimension. Here the ReLU is used as an activate function and it is expressed as

$$f_{conv}(x) = \max(0, x) \tag{6}$$

The ith feature map is obtained by the above process.

Primary capsule layer

It is a first capsule layer in which the CNN scalar feature is replaced by the capsules. A filter z_i multiplies m_i one by one with the stride of 2 and c_1 to create a q_i which indicates the ith feature map of the primary capsule layer. The range of q_i is calculated as

$$q_i = f_{conv}(m_{i:i+c1-1} \otimes z_i + b_i) \in R^{n-c-c1+1/2+1} \tag{7}$$

Where b_i is the bias, c_1 is the size of the filter. This equation is for L_1 times to obtain i^{th} capsule as $q_i \in R^{((n-c-c1+1)/2+1) \times L_1}$. If there are L_2 layer then the primary capsule layer is calculated as

$$Q = [q_{1,} q_2 .... q_{L2} \in R^{((n-c-c1+1/2+1) \times L_1 \times L_2} \tag{8}$$

Routing –by-agreement mechanism

The length of the capsule output is defined as the probability of features which are occurred in the present capsule. The function of the non-linear squashing is redistribution and compression to the input vector which is given below.

$$V_j = \frac{\| T_j \|^2}{1 + \| T_j \|^2} \frac{T_j}{\| T_j \|} \tag{9}$$

Where T_j and V_j are the input and output of jth capsule.

The vector calculation is split into routing process and linear combination and it is given as

$$T_j = \sum_i c_{ij} u_{j|i} \tag{10}$$

$$u_{j|i} = w_{ij} u_i \tag{11}$$

Where w_{ij} and u_i are the weight matrix and output of the ith capsule. $u_{j|i}$ is the prediction vectors and c_{ij} is a coupling factor which is found by iterative dynamic routing procedure. The coupling factor can be found by leaky-softmax and it can be written as

$$c_{ij} = leaky - soft\max(b_{ij}) \tag{12}$$

Where b_{ij} is a coupling factor logits and b_{ij} is updated by V_j and $u_{j|i}$, it is expressed as

$$b_{ij} = b_{ij} + u_{j|i}.v_j \tag{13}$$

Fully connected capsule layer

To enhance the ability of generalization of ACAE the dropout is introduced in the network. The capsule unit of the fully connected layer is fully connected whereas the primary capsule layer will be eliminated randomly with some probability. In this layer, the capsules routing-by-agreement and transformation matrix $w \in R^{H \times L_2 \times E}$ are multiplied to generate the last capsule $v_j \in R^{L2}$. Here, E is a category, H is the number of capsules and L_2 is the capsule dimension.

Finally the resources like power, space, time and frequency higher transmission data rate and throughput are allocated with the help of deep learning. With these resources, TAS process is employed.

3.2 System Model

Antenna selection is evaluated as a signal processing approach that enhances the performance of the MIMO system; Multiple-antenna systems are also called as MIMO used to enhance the reliability and capacity of radio communication. But, the multiple RF chains accomplished with multiple antennas are high cost with respect to hardware, power and size. Let us consider the massive MIMO system with transmit and receive antennas M_t and M_r where $M_r (M_r << M_t)$ the input and output relationship is illustrated as

$$R(t) = \sqrt{\frac{\rho}{M_t}} HV(t) + W(t) \tag{14}$$

Where $R(t) = [R_1(t), R_2(t), ...R_{Nr}(t)]^T$ is a vector of the received signal $V(t) = [V_1(t), V_2(t), ...V_{Nr}(t)]^T$ is a vector of the transmit signal and $W(t) = [W_1(t), W_2(t), ...W_{Nr}(t)]^T$ is a vector of the zero-mean. ρ is the average signal to noise ratio and $H \in C^{Mr \times Mt}$ is a channel matrix.

The transmitter should equally distribute their power to all the M_t without instantaneous channel state information (CSI). So the MIMO capacity for the channel matrix H, Eq. (1) can be represented as

$$C(H) = \log_2 \det\left(I_{Mr} + \frac{\rho}{M_t} HH^H \right) \tag{15}$$

Let us consider that the transmit antennas M_s are selected from M_t antennas then $M_t = M_s$. Therefore the full receiver antenna set can be utilized. When the channel is considered as slightly time-varying, therefore the instantaneous CSI can be received at the receiver with some uncertainty. Hence, the selection can be done at the receiver with sensible accuracy. Once the selection is completed, selected antenna indices are sent to the transmitter

through the limited feedback channel. Therefore the capacity of the channel after TAS is given as

$$C(H_{sel}) = \log_2 \det\left(I_{Mr} + \frac{\rho}{M_s} H_{sel} H_{sel}^{\ H} \right) \tag{16}$$

Problem formulation

Let us consider the antenna selection operator as given as.

$$\Delta = [\Delta_1 .....\Delta_{Mr}] \tag{17}$$

Where

$$\Delta_i = \begin{cases} 1, if\ the\ i^{th} antenna\ is\ selected \\ 0, else \end{cases} \quad i = 1,2,.....M_r \tag{18}$$

Therefore the capacity after TAS is calculated from Eq. (16) as:

$$C(H_{sel}) = \log_2 \det\left(I_{Mr} + \frac{\rho}{M_s} [H_{sel}^{\ H}\, 0_{M_t \times (M_r = L)}] \begin{bmatrix} H_{sel} \\ 0_{(M_r - L)M_t} \end{bmatrix} \right) \tag{19}$$

Define

$$\bar{H}_{sel} \begin{bmatrix} H_{sel} \\ 0_{(M_r - L)M_t} \end{bmatrix}_{M_r \times M_t} \tag{20}$$

Hence the relation among H_{sel} and H can be defined as

$$\bar{H}_{sel} = P_r.diag(\Delta).H \tag{21}$$

Where P_r is the row permutation matrix, $P_r^{\ H} P_r = I_{M_r}$ $diag(\Delta)$ is a $M_r \times M_r$ matrix diagonal with Δ_i is the entry of the diagonal. This provides

$$\bar{H}_{sel} \bar{H}_{sel}^{\ H} = H^H.diag(\Delta).P_r^{\ H}.P_r.diag(\Delta).H = H^H.diag(\Delta).H = H_{sel}^H H_{sel} \tag{22}$$

Therefore Eq. (16) will becomes

$$C(H_{sel}) = \log_2 \det\left(I_{Mr} + \frac{\rho}{M_s}.diag(\Delta).HH^H \right) \tag{23}$$

Where, selection problem in MIMI to increase capacity can be expressed as:

$$\text{Maximize: } \log_2 \det\left(I_{Mr} + \frac{\rho}{M_s}.diag(\Delta).HH^H \right) \tag{24}$$

Subject to: $\text{sum}(\Delta) = L$

$(\Delta_i) \in [0,1]$

The selection of the TAS is a NP-hard problem base on the Eq. (24). To deal with this issue, BRO is introduced to improve the computational efficiency.

3.3 TAS selection by BRO

Most of the metaheuristic algorithms are influenced by the social character and nature of the birds or animals. But, this BRO [27] optimization is influenced by a game that is "battle royale". This method is on the basis of population in which every individual is denoted by a soldier who likes to move towards the best place and live. Like other optimization techniques, this algorithm also initializes with a random population, and that is equally allocated among the problem space. Then each player or soldier attempts to attack the nearby player by shooting a weapon. Players who are in better positions damage their neighbours in the nearest position.

When one player is damage by some player, then the level of the damage is increased by 1. These interactions are computed by

$$yi.D = yi.D + 1 \tag{25}$$

Where $yi.D$ is the level of the damage of the ith player the between the population. Further, players need to switch their position at once after experiencing hurt and so damage the enemy from the opposite side. Therefore, for focusing on exploitation, the player who is damaged moves to a point somewhere among the best and previous position. These relationships are computed by

$$y_{dam,d} = y_{dam,d} + rand(y_{best,d} - y_{dam}, d) \tag{26}$$

Where $rand$ is the random number varies from [0, 1], $y_{dam,d}$ is the damaged player position in the dimension d. Further, if the players who are damaged can attack their enemy in the further iteration, $yi.D$ is reset to 0. The players arrive back to problem space after being killed is given below the expression

$$y_{dam,d} = r(Ub_d - Lb_d) + Lb_d \tag{27}$$

Where Ub_d and Lb_d are the upper and lower bound of the dimension d. In addition in all iteration Δ the possible problem search space led to shrinking down to the best solution. $\Delta = \log_{10}(\max circle)$ is the initial value, $\max circle$ is the maximum number of generation but $\Delta = \Delta + round\left(\frac{\Delta}{2}\right)$.

This iteration ensures exploitation and exploration. Hence the lower and upper bounds are updated as

$$Lb_d = y_{best,d} - SD(\overline{y_d}) \tag{28}$$

$$Ub_d = y_{best,d} - SD(\overline{y_d}) \tag{29}$$

Where $SD(\overline{y_d})$ is the whole population standard deviation in dimension d and $y_{best,d}$ is the best solution position. Further if the Ub_d and Lb_d exceeds the actual upper and lower bound then it is defined as the original Ub_d and Lb_d.

3.4 Fitness function generation

Here, each particle is evaluated using the fitness value. Based on that the TAS can be defined as

$$Fitness = \log_2 \det\left(I_{Mr} + \frac{\rho}{M_s}.diag(\Delta).HH^H \right) \tag{30}$$

Initialization: Randomly initialize the population, initialize all parameters.
Evaluation: The fitness function is evaluated by Eq. (30).
Updation: Shrink down the problem on the basis of Eq. (27). If the termination criterion is met, choose the best solution based on Eq. (28) and Eq. (29). If the criteria are not met then again repeat the procedure as a satisfied best solution being developed. The global best one among all the players is taken as the final solution.

3.5 Computational complexity

The computational complexity is based on the size of the population and a maximum number of iterations. Therefore it can be written in big notation as $O(n^2)$.

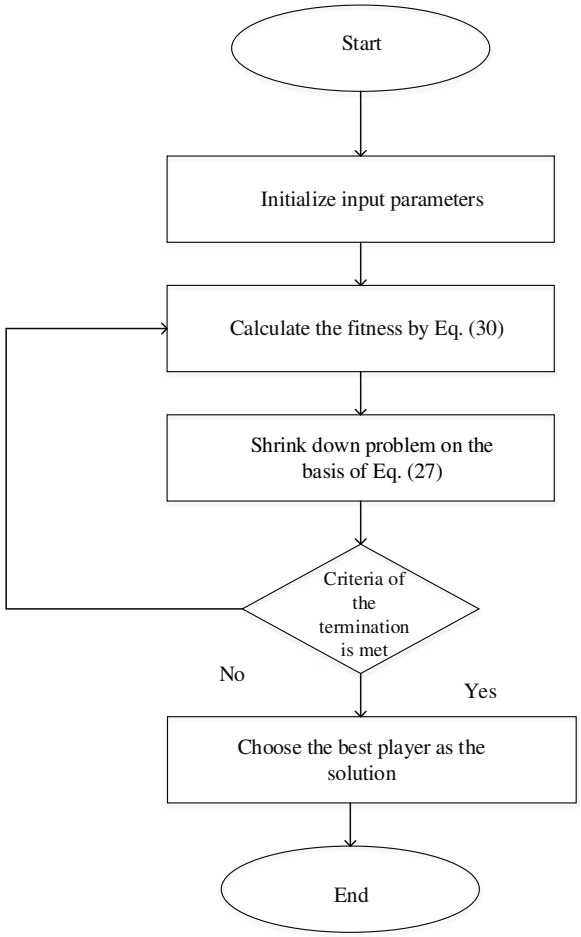


Figure 2: Flowchart of the developed TAS based on BRO optimization**.**

Figure 2 represents the flowchart of the proposed method. BRO optimization continuously generates new and better solution by updation. To apply BRO in TAS, the parameters like position and standard deviation are to be determined. To find the best individual solution fitness has to be calculated.

3.6 Application of the proposed massive MIMO for 5G.

5G networks are presently continue to be evaluated and their motive to be hundred times faster than the present 4G network. 5G networks provide data rates of about ten Gbps, high reliability and less latency.

Some significant advantages of the proposed massive MIMO of 5G are:

User experience: 5G improves artificial intelligence, virtual and augmented reality.

Energy efficiency: This network ensures more than 90% of the energy efficiency when compared to the 4G network.

Spectral efficiency: The proposed method based 5G network offers more network and spectral efficiency through its antenna array toward the user

Battery life: 5G offers nearly 10 years of battery life for IoT devices.

Coverage: The wave with high-frequency has a shorter wavelength and it is not able to travel to a long distance. Because of this there must be more BS in a smaller to provide a proper connection. More BS will increase the complexity and cost of the system.

Data rate: the data rate of the 5G is about 10 Gbps.

Security and user tracking: Massive MIMO offers more security because of its narrow beams and user tracking also more accurate.

Less fading: At the receiver, MIMO has more number of antennas which makes the system against fading.
Consumption of Low power: Massive MIMO is developed with lower power linear amplifiers, which discard the heavy electronic appliances in the system. Due to the low power amplifier the consumption of power will be minimized.

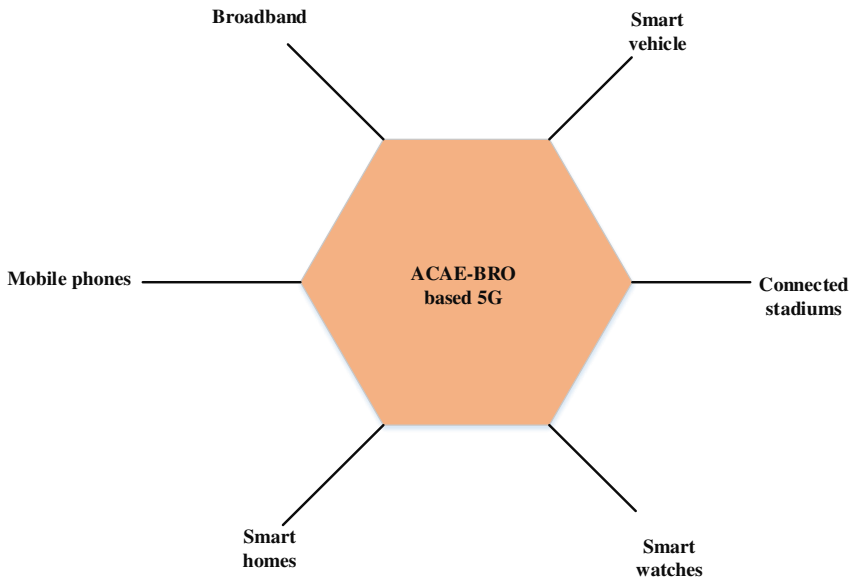


Figure 3: Various applications of ACAE-BRO based 5G.

Figure 3 shows the various application of ACAE-BRO based 5G.When implementing this proposed methodology, HD movies are downloaded in few seconds. This approach can support smart vehicles and large Internet of Things (IoT). The effective wireless methodology can improve the throughput without increasing the bandwidth.

4. Results and discussion

This section gives the performance analysis and discussion of resource allocation and TAS of the proposed scheme. The entire implementations have been processed on a system with 8 GB RAM and Intel Core i5 CPU with 3.0 GHz speed. To implement the proposed scheme, the MATLAB R2020 is utilized. Here the size of population (P) =100 and number of iteration (T) =100. Here the performance of the implemented model is compared against the existing approaches like Maximum Ratio Combing (MRC) [28], Exhaustive Search Algorithm [29] [30], Genetic Algorithm (GA) [29], Norm-Based Selection Algorithm (NBS) [29], Particle Swarm Optimization (PSO) [30], and zero Forcing (ZF) [28].

4.1Performance Metrics

The throughput is measured in bits per second $[b/s]$. EE is evaluated in bits per unit Joule $[b/J]$ and SE is measured in throughput per unit spectrum $[b/s/HZ]$. The formula for the calculation of SE and EE is given below.

$$SE = \frac{throughput}{bandwidth} \tag{31}$$

$$EE = \frac{throughput}{total\ power\ consumed} \tag{32}$$

4.2 Comparison of capacity, EE and SE

In this section the developed approach performance is compared against the conventional approaches with respect to capacity, convergence analysis, EE SE and Cumulative Distributive Function (CDF).

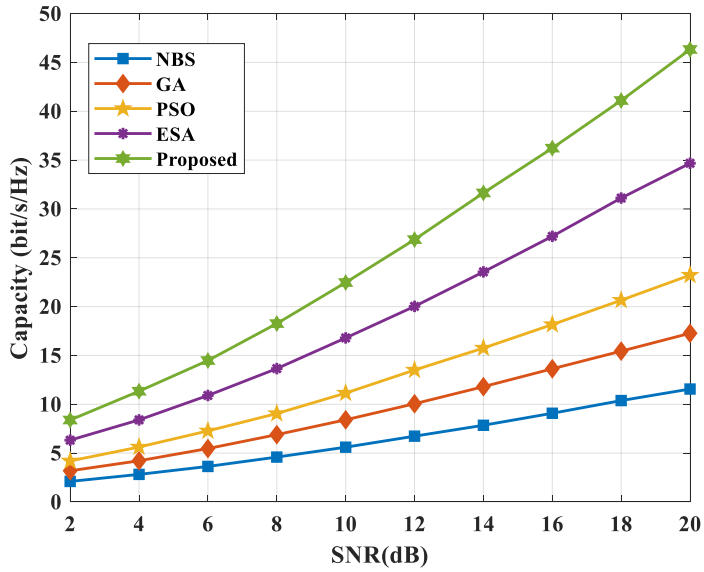
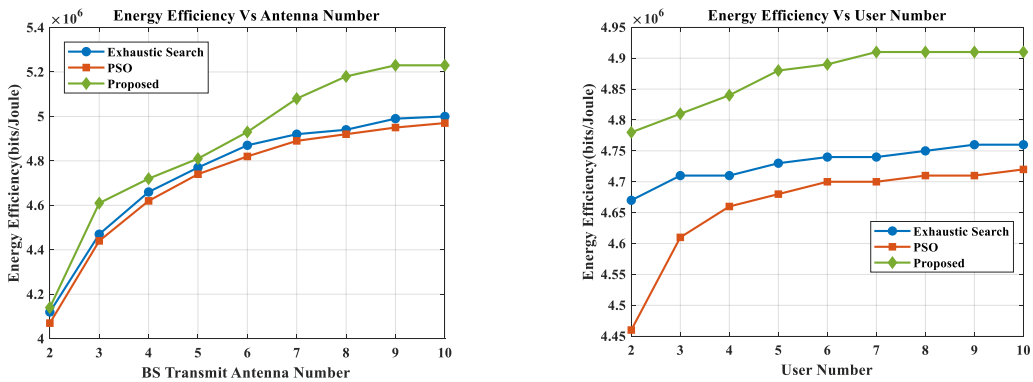


Figure 4: Capacity curve with respect to SNR

Figure 4 shows the capacity curve and SNR for various algorithms like exhaustive search algorithm (ESA), Genetic Algorithm, Norm-Based Selection Algorithm (NBS) are compared with the proposed method. Particularly when SNR=16dB the proposed method achieves the capacity of about 36. It is observed from the graph that the proposed method in all the SNR value achieves the better capacity while the other optimization achieves less capacity than the proposed algorithm.



(a) (b)

Figure 5: EE with respect to BS

Figure 5 shows the EE with respect to number of user and BS when the distance is 1km. The user number (K) and transmit antenna M_t cause the EE in a complicated way. These parameters have to be adjusted to improve EE. The performance of the developed approach is compared against PSO and ESO and the developed method shows the rise in EE. From figure 5(a), When BS=10, the proposed method achieves the EE of about 5.3×10^6 $[b/J]$ but the other

methods like PSO and ESO attains only about $4.9\times10^6\,[b/J]$ and $5.0\times10^6\,[b/J]$ respectively. Similarly from figure 5 (b), When BS=10, the proposed method achieves the EE of about $4.9\times10^6\,[b/J]$, but the other methods like PSO and ESO attains only about 4.67 $\times10^6\,[b/J]$ and 4.71 $\times10^6\,[b/J]$ respectively.

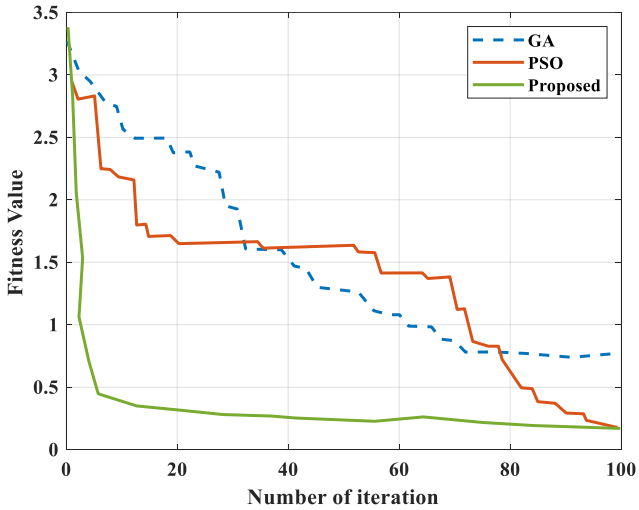
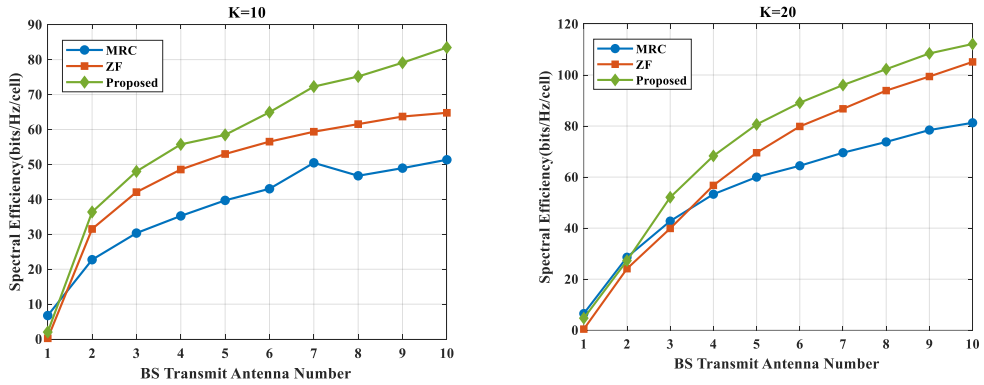


Figure 6: Convergence Analysis

Figure 6 depicts the convergence analysis of the developed method is compared with the conventional methods like PSO and GA for 100 runs with respect to number of iteration and fitness value. In 20th iteration, the fitness value of the GA is about 2.4, PSO is about 1.6 and proposed method is 0.3. Similarly in all iterations the fitness value is less for the propose method. Therefore it is proved that the proposed method converge faster than the other algorithms.



(a) (b)

Figure 7: Comparison of the SE with respect to BS

Figure 7 depicts the comparisons of SE against UEs and BS as constant when k=10, k=20. Here for all BS, the proposed method outperforms the MRC and DZF and achieves higher SE. For k=10, when $M_t = 2$ SE increases and reaches the maximum value of 38 and when $M_t = 10$, SE increases nearly 83 $[b/s/HZ]$, but other methods achieve less than the developed method. Thus the proposed method achieves maximum SE.

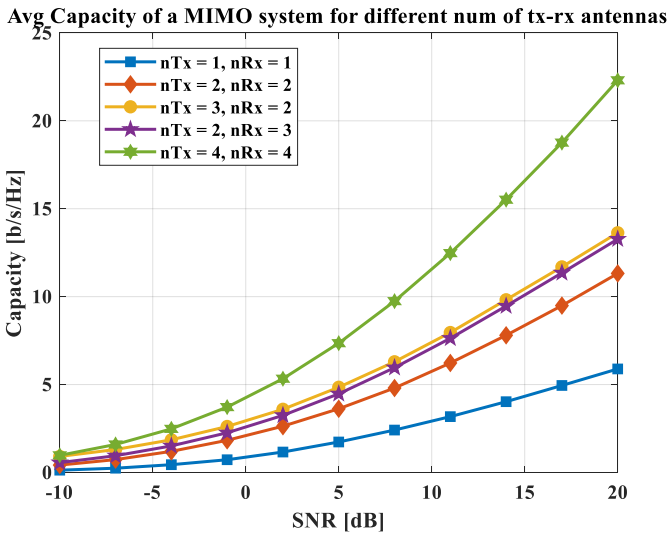


Figure 8: Average capacity of the MIMO for different transmitter and receiver

Figure 8: Average capacity of the MIMO for different transmitters and receivers with respect to the capacity. Implementation is done for various transmitter and receiver sides. From the result, it is seen that the capacity is enhanced because of the same number of antennas are employed in both the transmitter and receiver. Particularly when SNR=20dB the capacity for 4x4 is about $23[b/s/HZ]$. In all the cases the receiver and transmitter 4x4 achieve better capacity and 1x1 achieves less capacity.

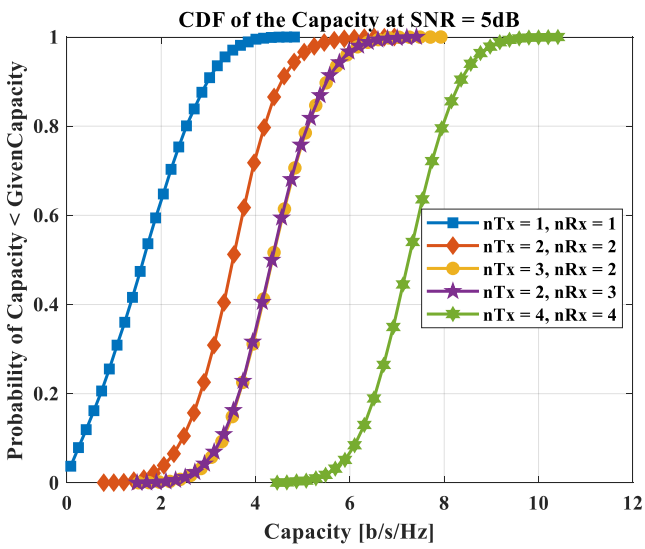


Figure 9: CDF of the capacity at SNR=5dB

Figure 9 shows the CDF of the capacity at SNR=5dB for 1x1, 2x2, 3x3 and 4x4. From the graph, it is illustrated that when the SNR value is increased capacity also increased. When the probability of capacity is 0.2, for 1x1 the capacity is 0.9, for 2x2 the capacity is 2.5, for 3x3 and 2x3 the capacity is 3.8 and finally for 4x4 the capacity is 6.2. It is proved 4x4 achieves higher capacity than other cases respectively.

5. Conclusion

This paper had proposed both the Resource Allocation (RA) as well as the antenna selection process of wireless communication in mm-wave using massive MIMO technology. Two different solutions are developed for this research such as the Deep Learning method for

efficient resource allocation process and optimization algorithm for Transmit Antenna Selection (TAS) process. Here, the RA process is done with the help of Attention Based Capsule Auto-Encoder (ACAE) architecture which allocates the radio resources like power, space, time and frequency to all the available users in the system. Further, Battle Royale Optimization (BRO) algorithm is utilized to select an efficient antenna from multiple antennas at BS. This optimization algorithm optimally selects an efficient antenna so that, user equipments (UEs) can create high quality links and achieves a reduced power consumption rate of the whole architecture. The overall system performance is based on the selection of optimal antenna which in terms enhances Spectral Efficiency (SE), Energy Efficiency (EE), and capacity of the MIMO technology. In this way, both RA and optimal antenna selection schemes are performed to maximize the overall performance of wireless communication with massive MIMO technology for 5G wireless communication applications. The implementation of the proposed methodology is evaluated on MATLAB 2020a. Finally, the performance of the developed method is improved with respect to capacity, EE and SE. In the future, another novel optimization technique will be used to improve the EE, SE and capacity. In addition, the antenna selection will be applied to both transmitters and receivers.

Compliance with Ethical Standards

Funding: No funding is provided for the preparation of manuscript.
Conflict of Interest: Authors CHARANJEET SINGH, P C KISHORERAJA declares that they have no conflict of interest.
Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.
Consent to participate: Two authors have equal contributions
Consent to Publish: Reviewer and Editors can publish this work
Authors Contributions: All authors are equal contributions in this work
Availability of data and materials: No data Availability
Acknowledgement: I sincerely thanks P C KISHORERAJA for their guidance and encouragement in carrying out this research work.

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