Improved Butterfly Optimization Algorithm for Energy Efficient Antenna Selection Over Wireless Cellular Networks

Isabel Menacho Vargas[1*], Carlos Luy-Montejo[2],
Lourdes Ivonne del Carmen Alcaide-Aranda[3], Doris Isabel Goicochea Parks[4],
Yoni Magali Maita Cruz[5], Jessica Paola Palacios-Garay[6] and
Aracelli del Carmen Gonzales-Sánchez[7]

[1*] Universidad Nacional Mayor de San Marcos, Lima, Perú. imenachov@unmsm.edu.pe,
Orcid: https://orcid.org/0000-0001-6246-4618

[2]Universidad Privada del Norte, Lima, Perú. fracarlitos@gmail.com,
Orcid: https://orcid.org/0000-0003-0824-7959

[3]Universidad Nacional Mayor de San Marcos, Lima, Perú. lalcaidea@unmsm.edu.pe,
Orcid: https://orcid.org/0000-0003-0304-8344

[4]Universidad Nacional Jorge Basadre Grohmann, Tacna, Perú. dgoicocheap@unjbg.edu.pe,
Orcid: https://orcid.org/0000-0002-5628-2153

[5]Universidad César Vallejo, Lima, Perú. ymaitacr27@ucvvirtual.edu.pe,
Orcid: https://orcid.org/0000-0002-6961-7231

[6]Universidad Nacional Mayor de San Marcos, Lima, Perú. jpalaciosg@unmsm.edu.pe,
Orcid: https://orcid.org/0000-0002-2315-1683

[7]Universidad César Vallejo, Lima, Perú. agonzalessa@ucv.edu.pe,
Orcid: https://orcid.org/0000-0003-0028-9177

Received: April 10, 2023; Accepted: June 06, 2023; Published: June 30, 2023

Abstract

The emergence of a new trajectory in wireless networks can be attributed to the assessment of mobile devices and applications in the present decade. A recently developed approach that combines energy harvesting with large-scale multiple antenna technology has emerged as a promising means of enhancing energy efficiency through the utilization of renewable energy sources and the reduction of transmission power per user and per antenna. Multiple Input Multiple Output (MIMO) refers to systems with more than one antenna element in both the transmitting and receiving sections. In the existing system, energy efficiency and optimal antenna selection is not achieved in MIMO system. Hence, in this work, Improved Butterfly Optimization (IBFO) algorithm-based antenna selection is proposed. Using adaptive hybrid analog-digital beamforming, this research evaluates a fifth-generation (5G) MIMO millimeter wave (mmWave) wireless cellular beamforming system. In order to achieve the highest possible level of energy efficiency, finding the best transmit power, number of active antennas, and antenna subsets at both transmitter and receiver is the main focus. In order to maintain a higher data rate for wireless access, it is also employed to provide excellent Quality of Service (QoS). The optimization method uses sub-channel allocation, MIMO systems, and bandwidth allocation to offer the desired data rate for applications in real time. The proposed IBFO

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 14, number: 2 (June), pp. 121-136. DOI: *10.58346/JOWUA.2023.I2.010*

*Corresponding author: Universidad Nacional Mayor de San Marcos, Lima, Perú.

model improves wireless power allocation schemes by using the best fitness value and optimal antenna elements to lower Bit Error Rate (BER), energy consumption, sum rate, throughput, and spectral efficiency.

Keywords: Wireless Cellular Network, Antenna Selection, Improved Butterfly Optimization (IBFO) Algorithm, Sub Channel Estimation.

1 Introduction

Mobile services with no latency and high data rates are made possible by fifth-generation (5G) broadband wireless cellular networks (Nomikos, N., 2019). To support the 5G vision in this environment, a number of unique technologies have been introduced: mmWave (millimeter wave) transmission (Larsson, E.G., 2014) Architectures that use both massive multiple input multiple output (MIMO) and non-Orthogonal Multiple Access (NOMA). In the latter case, base stations (BSs) in cellular networks have several antenna arrays carefully placed. Mobile stations (MSs) that need high data rate services will benefit from this deployment. Making highly focused beams that eliminate multiple access interference facilitates this.

It is not safe to assume that the long-term fading coefficients between a user and all of the array's antennas would remain constant over time because of the vast size of the antenna array that is used by the XL-MIMO system (Ali, A., 2019) and the many spatial non-stationarities that it has. The work on massive MIMO is based on the traditional idea of a massive MIMO system, which differs from the XL-MIMO scenario. A very wide array's various areas are demonstrated in (De Carvalho, E., 2020) by experimental measurements to have varied propagation pathways, and in certain situations, the terminals may only be able to view a visibility region (VR) of the array. The non-stationarity characteristics of this novel situation are also discussed in terms of how they alter numerous critical design aspects. A MIMO antenna is seen in Fig. 1.

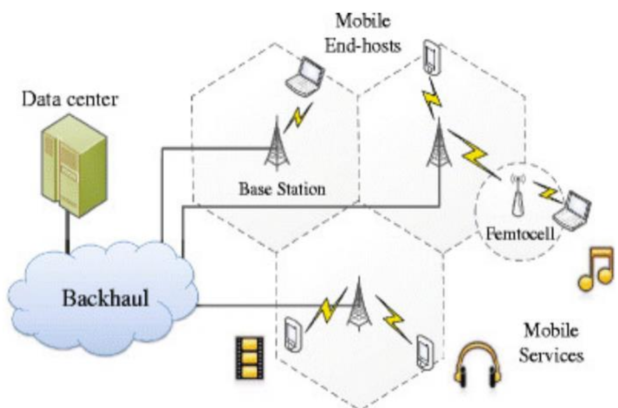


Figure 1: Example of Wireless Mobile Network

Generally speaking, antenna selection technology, the optimal solution involves establishing connections between a limited number of radio frequency circuits and high-quality antennas. On the assumption that the antenna's spatial range fulfils signal multiplexing criteria and is based on the chosen MIMO system's maximum capacity criterion, the study employs a combined transmit and receive antenna selection method with minimal computing complexity and great performance (Ngo, H.Q., 2013). By continuously deleting a row and a column of the comparable decrement channel matrix, which removes a pair of transmitting and receiving antennas, we may apply a simplified channel capacity equation from the conventional capacity formula and the complete MIMO channel matrix.

The common method for adjusting the amplitudes and phases of the broadcast signals in classic Multi-User (MU) MIMO systems in order to achieve optimal beamforming is Fully Digital (FD) precoding. However, the FD approach would need a lot of computing and hardware resources since a massive MIMO configuration has the same number of radio frequency (RF) chains as antennas. It concentrated on suboptimal beamforming algorithms based on the Hybrid Beam Forming (HBF) strategy, which combines the analog RF precoder with the digital baseband precoder in a hybrid precoding architecture (Lavdas, S., 2021). Therefore, Low-dimensional digital precoder implementation requires fewer RF connections. The effectiveness of a low-complexity HBF structure in large MIMO mm Wave multicellular orientations is assessed in this paper.

The main aim of this research work is optimal antenna selection in wireless cellular network. There are several research and methodologies introduced but the energy consumption is not achieved significantly. To overcome the abovementioned issues, in this research, Improved ButterFly Optimization (IBFO) algorithm is proposed to improve the overall network performance. The main contribution of this research is construction of system model, energy model, antenna selection and sub channel allocation. The proposed method is used to provide better results using effective algorithms for industrial mobile devices

Following is how the remaining work is arranged: In Section 2, there is a short discussion of a few pieces of literature on antenna selection. Section 3 of the proposal provides details on the IBFO algorithm technique. Experimental results and performance analyses are presented in Section 4. Section 5 presents the results.

2 Related Work

In (Zhang, J., 2019), Zhang et al (2019) based on a unique hardware taxonomy, provides a complete view of hybrid beamforming for 5G and future mm-wave systems. We examine several approaches from three crucial angles using a practical approach: 1) efficiency of the hardware, i.e., the necessary hardware parts; 2) Efficiency of the accompanying beamforming algorithm in terms of computing; and 3) a key performance indicator is the achieved spectral efficiency. Promising options for hybrid beamforming in future wireless networks are found via systematic comparisons that show how these three design characteristics interact and trade off one another.

In (Ioushua, S.S., 2019), Ioushua et al (2019) considered the part of massive MIMO communication known as the data phase when RF chains rather than antennas are used by the transmitter and receiver. We construct hybrid beam formers to decrease data inaccuracy and discuss additional relevant methods. In order to approximate the ideal completely digital precoder with a workable hybrid one, we provide a framework for the hybrid precoder. In order to optimize this matrix and the hybrid precoder alternatively, we make use of the completely digital precoder's limited uniqueness up to a unitary matrix. With no appreciable increase in complexity, Our Alt-MaG method beats current methods. We also present a new Alt-MaG application termed minimal gap iterative quantization (MaGiQ), which has lower complexity and mean squared error (MSE) than other traditional techniques for a limited number of RF chains. MaGiQ has also been shown in certain cases to be equivalent to the ideal totally digital solution. Utilizing the MSE objective's structure, we create a greedy ratio trace maximization method for combiner design that, in a variety of conditions, achieves low MSE. Each of our methods is compatible with a variety of hardware architectures.

In (Phyo, Z.C., 2016), Phyo et al (2016) studied MIMO system downlink hybrid analog-digital beamforming approach. Analog, digital, and hybrid beamforming must be assessed when employing uniform and non-uniform linear arrays. In order to calculate and compare the procession times for each scenario in this system, the base station first assumes perfect channel estimation. Binomial and Dolph-Chebyshev arrays are used for non-uniform linear arrays to decrease sidelobes and improve the directivity of the array pattern, respectively. The number of radio frequency (RF) chains may be changed, it is possible to examine hybrid, fully digital, and totally analog beamforming. Simulation findings demonstrate that hybrid beamforming's performance is quite comparable to that of completely digital beamforming. Additionally, the hybrid scenario may be simplified while still attaining comparable spectral efficiency to the completely digital one, based on the program's execution duration, which represents the system's complexity. According to simulation data, non-uniform linear arrays perform much better than uniform linear arrays when used for hybrid beamforming. As a result, we may draw the conclusion that hybrid beamforming, which uses non-uniform linear arrays, can approach completely digital beamforming solutions while needing less power complexity.

In (Hu, B.B., 2014), Hu et al (2014) suggested that MIMO has significant advantages in energy efficiency and spectrum efficiency, needing tens or hundreds of base station antennas supporting a far fewer number of terminals than conventional MIMO technology. Large antennas produce RF chains. Because RF chains use a lot of power and are expensive, Massive MIMO wireless communication systems need antenna selection on both ends. Massive MIMO wireless communication systems use a convex optimization-based energy-efficient antenna selection method. If the cell's channel capacity rises over a specific level, the number of transmit antennas, a subset of transmit antennae, and servable mobile terminals (MTs) are concurrently altered to improve energy efficiency. The detailed proof is given for the joint optimization issue. Analyses and numerical simulations are used to confirm the method. When compared to no antenna selection, a good performance boost in energy efficiency is attained.

In (Eskandari, M., 2018), Eskandari et al (2018) investigated a fresh approach to energy efficiency (EE) maximization and power distribution difficulties in point-to-point MIMO spatial multiplexing systems. In contrast to conventional energy-efficient optimization strategies, which require repetitive numerical calculations, we present a closed-form optimal solution that illustrates how system variables like circuit power and channel conditions impact the ideal EE. Additionally, we specify a maximum EE for the fully passive transmit antenna using the closed-form function. We also use a novel antenna selection approach based on the obtained upper limit that, although much less complicated, provides almost the same efficiency as the ideal solution.

In (Cheng, Y., 2018), Yongqiang et al (2013) investigated the non-convex properties brought on by it is unable to directly solve because of the discrete binary antenna selection factor, the issue of receive antenna selection in wireless MIMO communication systems is a problem for capacity. Integer programming optimization may solve this issue. To solve this problem, the Particle Swarm Optimization (PSO) approach links the objective function with the capability of the chosen antenna subsection represented by the particle, using the discrete binary antenna selection factor as the particle. PSO is a computationally efficient method. In order to satisfy the criteria that the number of selected antennas must remain constant, the particle components are free to move between [0 1], and the position of the top elements is used as the index of the antenna subsection to be activated. Then, by looking for the global optimum particle in PSO, one may discover the best antenna subset. Numerical findings demonstrate that the PSO approach works effectively for the benchmark function and our antenna selection situation.

In (Xu, D., 2019), Cheng et al (2018) investigated the issues with joint user pairing and subchannel allocation (JUP-SA) in a NOMA system with multiple subchannels and many users. In order to maximize the minimal user diversity order, we first assess the uplink using JUP-SA. The worstperforming user's outage probability restricts the system's viable diversity order. After considering the system's downlink, a JUP-SA method optimizes the least diversity order. Then the simulation results are used to generate and verify a worst-case outage probability statement in closed form. According to numerical results, both uplink and downlink NOMA methods may achieve the same diversity order as the exhaustive search.

In (Gao, H., 2021), Liu et al (2016) investigated large Spectral Efficiency (SE) and Energy Efficiency (EE) are the options available in MIMO systems with linear precoding and transmit antenna selection when taking into account circuit power consumption and large-scale fading. The EE and SE are optimized for transmit antennas and power; hence the EE-SE trade-off is set up as a mixed-integer-continuous-variable multi objective optimization (MOO) problem. The obtained EE-SE relations are used to assess the Pareto front's EE-SE trade off characteristics. Two algorithms are created in order to resolve the challenging MOO problem: WS-PSO and NBI-PSO are the algorithms under consideration. The simulations show that both approaches may reach the Pareto optimum trade-off between energy efficiency (EE) and spectral efficiency (SE). Furthermore, it is observed that the NBI-PSO algorithm produces solutions that are more evenly distributed compared to the WS-PSO algorithm.

3 Proposed Methodology

In this study, wireless cellular networks are used to pick the best antenna using the Improved Butterfly Optimization (IBFO) method. Antenna selection, sub-channel allocation, a system model, and an energy model are all included in this paper. In Fig. 2, the suggested framework's general block diagram is shown.

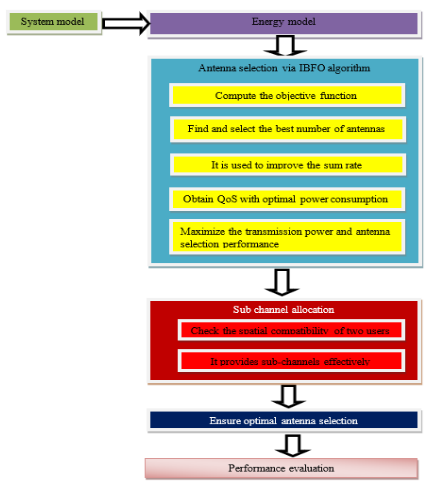


Figure 2: The Entire System is Shown in the Block Diagram

System Model

In this work, MIMO mmWave 5G wireless cellular orientations network is considered over a bandwidth of *B* Hz. K users have double antennae, while N users have single antennas. Co-time Co-frequency Full Duplex (CCFD) mode is used by the BS and users. The same radio band is used by both the BS and users. At the BS, *Mt* (*Mt* <*M*) while some Mr. antennas receive information, others send messages. By using various antennas, the users concurrently broadcast and receive data. The time slot indicated by the letter "T" in which this block of symbols is conveyed to the recipient may be characterized by the following system model:

$$Y = N + H * X \qquad (1)$$

The received symbol matrix, denoted as Y with dimensions rxt, is associated with the transmitted code word represented as X with dimensions txt. The noise matrix is denoted as N, while the channel coefficient matrix for Rayleigh fading is denoted as H. Since all channels are Rayleigh fading channels and global channel state information (CSI) collection is theoretically conceivable (Rawat, D.B., 2017). In one time period, the CSI between two nodes is unchanged; $hBS\_Uk \in C1 \times Mt$ The term "CSI vector" refers to the channel state information vector that represents the communication link between the transmitting antennas of the BS and the user k ($k = 1, 2, \ldots, K$), the BS and consumers communicate using CCFD massive MIMO mm Wave 5G wireless cellular technology in the same time-frequency domain. In order to maintain a realistic perspective, at valid nodes, we account for incomplete self-interference cancellation.

Energy Model

Every active antenna in real-world systems needs its own RF chain. The overall power consumption is roughly represented using the usual circuit power consumption model (Marinello, J.C., 2020), which we apply $P_{tot} = \frac{B.P_t}{\eta} + N_t.P_{Bc} + P_{etc}$The first term $\frac{B.P_t}{\eta}$ the power amplifying devices' power consumption, and η is the efficiency of the power amplifier. $P_{Bc} = P_{DAC} + P_{mix} + P_{filt}$ The power consumption associated with each active antenna at the base station is indicative of the circuit's representation. P_{etc} reflects the power consumption of the other circuit.

Antenna Selection Via IBFO Algorithm

Antenna selection in this study is carried out using the IBFO method. Each user is given an equal amount of power in order to estimate the total number of ideal antennas. Based on the assigned wattage, the user calculates the number of antennas. The suggested technique is utilized to choose the antenna and determine the broadcast power allotted. These items can increase the system's total rate and reduce power consumption. The nodes are chosen for antenna selection based on transmission power consumption and high energy efficiency values (Khalid, S., 2020). The proposed technique also significantly reduces feedback overhead, which is essential for attaining high capacity and low CPU time antenna selection. The linear procedure of the base station is shown in block diagram form in Fig. 3.

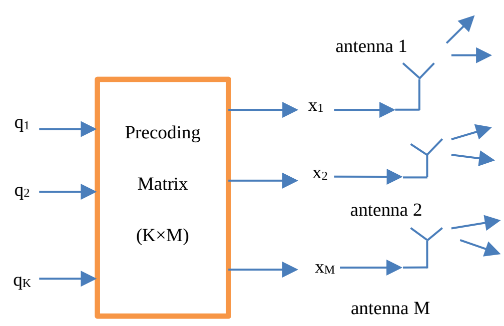


Figure 3: Block Diagram of Linear Procedure of the Base Station

The ideal amount of power allocation is calculated using the projected BER value. One method for estimating the generalized BER value is

$$g(\sigma 1, p1) \approx p \times \exp\{-q \times \sigma 1 \times p1\} \qquad (2)$$

$$\text{Where } \sigma 1 = \frac{1}{(2^m - 1)\sigma^2 \sum_{n=0}^{N_r - 1} |w^{(l,n)}|^2}$$

The modulated symbol's total number of bits is denoted by the variable Pl, while the transmit power of the lth antenna is represented by m. The global power cannot be derived in the domain space under consideration when the transmit power is distributed uniformly. Because of this, the best power allocation utilizing the BER expression is obtained using the suggested IBFO method.

The fragrance emitted by a butterfly exhibits a certain level of intensity that is positively associated with its fitness. In other words, as a butterfly transitions between different locations, its fitness level will correspondingly fluctuate. Three key concepts are used to define the whole notion of detecting and processing the modality in the IBFO algorithm: sensory modality (c), stimulus intensity (I) and power exponent (a) for best mobile node selection (Arora, S., 2019). For the selection of nodes from a wireless cellular network, I in the IBFO Algorithm is connected with fitness. In the IBFO Algorithm, as illustrated by the equation, these notions are used to construct the fragrance based on the stimulus's physical strength (3),

$$f = cI^{a} \quad (3)$$

Where f is the size of the scent as perceived by other butterflies, or how strong the fragrance seems to be, c is the sensory modality that uses the shortest route to produce signals, In the power exponent relies on modality and stimulus intensity. Thus a & c in the range $[0, 1]$. On the other hand, if $a = 0$, it implies that the other butterflies are completely incapable of smelling the fragrance that any particular butterfly produces. As a result, the parameter affects how the algorithm behaves. c is a vital parameter for determining the IBFO algorithm's convergence speed and is another significant parameter. To demonstrate search algorithms, the following butterfly attributes are idealized:

1. Every butterfly should release a scent that will help it survive (mobile nodes) to attract each other (mobile nodes).
2. The butterfly with the greatest scent will fly.
3. The butterfly's sensory intensity depends on the objective's landscape.

IBFO comprises three phases: Initialization, Iteration, and Final. Each time IBFO is run, the initialization phase is carried out first, followed by repeated searches for optimum nodes, and lastly, the method is ended when the best solution for optimal selection has been discovered. In the initialization step, the IBFO algorithm's solution space is used to calculate the shortest distance. Additionally, the parameters' allocated values for IBFO (Tubishat, M., 2020). In the antenna selection search space, the placements of butterflies (mobile nodes), together with their fragrance and fitness values, are created randomly. The algorithm begins iteration after start-up. During each iteration, the butterflies within the solution space for antenna selection undergo movement to new positions, followed by the evaluation of their respective shortest distance values. First, according to the method, several locations in the solution space are used to determine butterfly fitness values. When this happens, these butterflies will use equations to produce smell where they are (4). The butterfly advances in the phase of global search in the direction of the best answer (g∗) (optimal nodes) which an equation may be used to depict (4),

$$x_i^{t+1} = x_i^t + \left(r^2 \times g^* - x_i^t\right) \times f_i * ECE_W \quad (4)$$

where x_i^t the resolving vector x_i the iteration number for i[th] butterfly t. Here, g^* identifies the current iteration's top-performing node solution that was determined after considering all other options. i[th] butterfly-like fragrance is shown by f_i and $r \in [0, 1]$ is an arbitrary number Equation (5) may be used to describe the local search phase,

$$x_i^{t+1} = x_i^t + \left(r^2 \times x_j^t - x_k^t\right) \times f_i * ECE_W \quad (5)$$

where x_j^t and x_k^t are the antenna selection solution space's j[th] and k[th] butterflies. If x_j^t and x_k^t belongs to the same swarm and $r \in [0, 1]$ becomes a local random walk if is a random number. For the best node selection from the supplied network, butterflies may explore locally and worldwide for food and a mate. In IBFO, switching from a common global search to an intense local search is done using the switch probability p. The iteration phase is carried out until the halting conditions are not satisfied. After iteration, the approach yields the best answer. To choose the ideal number of nodes in the given arrangement, the IBFO algorithm's node weight is also applied in equation (5). With the supplied wireless cellular network, the IBFO algorithm concentrated on enhancing the routing process by utilizing the best antenna selection. Cross Entropy (CE) is a statistical technique for calculating the distance between two sample distributions, reducing this distance in an optimization problem to find the ideal probabilistic distribution parameters. The CE approach offers high resilience, outstanding flexibility, and a solid capacity to do global searches.

$$CE = \frac{1}{N}\sum_{i=1}^{N} I_{s<r}\frac{f(x^i,v)}{g(x^i)} \qquad (6)$$

where x^i represents a representative sample chosen at random from $f(x;v)$ sampling density is very important $g(x)$. To determine the ideal significance sampling density, the distance between two sample distributions is calculated using the Kullback-Leibler divergence, or cross-entropy.

Algorithm 1 depicts the general phases that make up the proposed IBFO algorithm. the number of nodes in the specified network (Step 1), and then the stimulus intensity, is used to construct the starting population in Algorithm 1. I_i at x_i (Step 2) depending on the sensor modality to calculate c, power exponent a (Step 3). By using the quickest route, these components are produced. Then, halting conditions are applied (Step 4), and the fragrance value is calculated for each butterfly in the network (Step 6). The best node in the population is then found (Step 8), and a random number, r, is created (Step 10). If $r < p$ then use equation (5) to go in the direction of the best butterfly; else, walk randomly. Then, after updating a value (Step 17), assess people in light of their new positions (Step 18). Finally, use the end while command (Step 19) to finish the procedure. Fig. 4 depicts the suggested IBFO algorithm's flowchart.

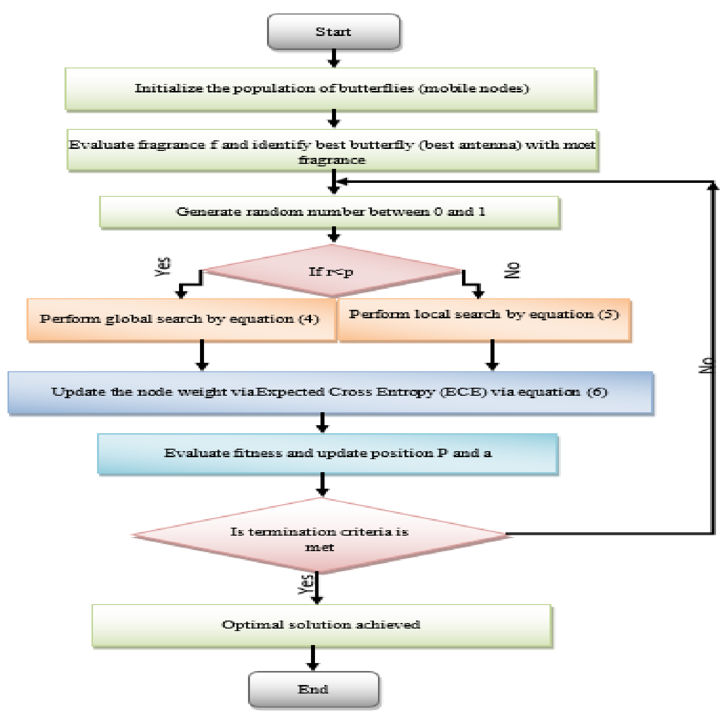


Figure 4: Flowchart IBFO Algorithm

Algorithm 1: Improved Butterfly Optimization (IBFO) Algorithm
Input: WMN with number of mobile nodes (multiple users and antennas)
Objective function: Higher sum rate and lower energy consumption
Output: Best no.of antennas selection

1. Generate initial population of n butterflies $x_i = (i = 1,2, \dots, n)$ via number of mobile nodes in the network
2. Stimulus Intensity I_i at x_i
3. The power exponent a, switch probability p, and sensor modality c.
4. when the halting requirements are not satisfied,
5. Do for each population of butterflies f.
6. Calculate fragrance for f using equation (2) and generate weight via entropy by equation (6)
7. End for
8. Finding the ideal butterfly (best antenna in mobile node)
9. Do for each population of butterflies f.
10. Generate random number r
11. If $r < p$ then
12. Equation (4) directs you to the ideal butterfly (best mobile nodes) and generate weight via entropy by equation (5)
13. Else
14. Use the equation (5) to move arbitrarily
15. End if
16. End for
17. A value should be updated
18. Individuals (nodes) should be evaluated in light of their new position

In this work, assigning and determining the chicks using the random position of the antennas in MIMO mmWave 5G wireless cellular orientations. The chicken with best fitness value is updated for improving the suitable antenna which is described in the Algorithm 1. Compute the best values for all users and find the best butterflies (antennas) which have global best searching food mechanism fitness value. The IBFO algorithm is used in the proposed system to identify antenna combinations that optimize transmission power while using a minimal number of chosen antennas. In order to maximize fitness, the IBFO the transmission power and antenna selection performance over the MIMO systems

Sub Channel Allocation

In this work, sub channel allocation increases the MIMO mmWave 5G wireless cellular orientations performance. Adaptive antenna arrays at base and mobile stations may increase QoS and system capacity in MIMO mm-Wave 5G wireless cellular systems. To broadcast the MIMO mm Wave block symbols, the highest-eigenvalue subcarriers are always used in adaptive antenna-array-based MIMO systems. For broadband MIMO wireless transmission systems, dynamic spatial sub-channel allocation with adaptive beam shaping is investigated (Tejera, P., 2006). The suggested system dynamically selects the ideal spatial sub-channels to transmit MIMO block symbols after choosing the eigenvectors associated with the relatively high spatial sub-channel eigenvalues to create the beam-forming weights at the mobile and base stations. The results demonstrate that the proposed system outperforms an adaptive antenna-arrays-based MIMO mm Wave 5G wireless cellular orientation system that does not employ dynamic spatial sub channel allocation in the presence of multipath fading channels. The suggested method outperforms adaptive antenna-array-based MIMO systems in terms of channel estimate accuracy and is less susceptible to feedback latency in rapidly changing channels.

Our zero-forcing allocation technique is equal to a MIMO mmWave channel Singular Value Decomposition (SVD) that does not need the sequential encoding feature if all receive antennas can work together. Our technique is equal to a Zero-Forcing with Successive Encoding Approach (ZF-SE) with optimum encoding order and user option, however, if cooperation among receive antennas is not available. In intermediate scenarios, wherein cooperatively receive antennas are organized into groups, the MIMO channels associated with these groups exhibit effective diagonalization. This occurs when only groups of antennas are permitted to engage in cooperation with each other. Cooperative zero-forcing with consecutive encoding and allocation is the name we give to our method because it makes advantage of the receive antennas' capacity for collaboration and successively allots sub channels to users.

The block-ZF-SE technique incorporates two parameters that can be optimized to achieve the objective of maximizing the sum rate. As stated earlier, the algorithm assigns a certain number of subchannels to an individual user, which is determined by the rank of its projected channel matrix during each iteration. In the event that certain subchannels exhibit weakness, it becomes evident that the current situation is suboptimal. In this particular scenario, their overall impact on the aggregate rate may be relatively insignificant, yet they exert substantial limitations on the subchannels of users that are subsequently encoded. The encoding order is considered the second parameter. In the subsequent section, an algorithm is presented within the framework of the ZF-SE method, which aims to guide users in order to achieve the maximum attainable sum rate. Zero-Forcing with the Successive Encoding and Successive Allocation Method, or ZF-SESAM is the name of the approach used in this research. The sequential assignment of subchannels to specific users is the method used in this case. This algorithm's criteria for sub channel allocation, together with each step's assignment of only one sub channel to a specific user,

To optimize the utilization of spatial processing capabilities at the transmitter and receiver, wireless communication systems require novel channel allocation techniques for multi-user MIMO processing algorithms. The task of identifying the optimal solution for a particular user group while maintaining cost-effectiveness in computing is a complex endeavour. This is primarily due to the additional variable introduced by spatial processing at the receiver, which further complicates the standard channel allocation problem. Subchannels in the frequency and spatial domain are given to each receiver in order to optimize all rates conveyed over the channel, under the assumption that the transmitter of a Gaussian broadcast channel holds entire channel state information. Each vector channel should be transformed into a collection of scalar channels, according to the recently proposed generic sum capacity maximizing technique. A two-step heuristic is suggested in this study. The first step computes a metric that gauges two users' geographic compatibility. After maximizing the total of the compatibility metrics across all groups, the users are divided into shared channels in the next stage. Additionally, it offers the option for a single user's sub-channels (from various multipath components) to not necessarily share the same time-domain channel. These methods have a reasonable processing cost while yet being pretty near to the ideal answer in simulations.

4 Simulation Result

A concurrent execution of separate Monte Carlo (MC) simulations has been built as a 5G system-level simulator. With a two-tier wireless cellular orientation, MSs are evenly distributed to achieve this. Requests from each MS Rk Mbps ($1 \leq k \leq K$) it may be feasible to appropriately allocate Physical Resource Blocks (PRBs) and determine the modulation order for each PRB based on the serving BS (5G NR Physical Channels and Modulation, 2018). In order to enhance overall throughput while minimizing downlink transmission power and blocking probability, it is imperative to implement optimization strategies, adaptive beamforming and subcarrier allocation, which will be discussed in the next section, are used (*BP*)

The existing methods are such as NOMA (Xu, D., 2019), Adaptive Hybrid Beamforming (AHB) (Lavdas, S., 2021) and BER, sum rate, energy use, spectrum efficiency, and throughput measures were used to assess the suggested IBFO algorithms.

Bit Error Rate (BER)

The number of error bits detected in a unit of time is known as the BER

$$\text{BER}=\frac{number\ of\ bits\ received\ in\ eror}{tota\ lnumber\ of\ bits\ transferred} \quad (7)$$

Sum Rate

The sum rate in a network is defined as the aggregate of all communication rates occurring within the network. The statement is pretty self-evident: The more time your nodes can communicate, the more data they can transfer

Energy Consumption

The most critical metrics in the mmWave 5G wireless cellular orientations are Energy Efficiency (EE). Energy efficiency trade-offs for MIMO mm Wave uplink transmission must be calculated by balancing the number of base station antennas against the number of users that are actively using the network (Akin, O., 2022). It is possible to define the efficiency of an antenna as the ratio between the power that is provided to the antenna and the power that is reflected away from the antenna. A considerable amount of the power that was originally given to the antenna is emitted or radiated in a direction that is different from its input. This is the defining characteristic of an antenna that has a high level of efficiency.

Spectral Efficiency

The total spectral efficiency of the transmissions inside a cellular network's cell is what we often refer to when we use the term "spectral efficiency." In bits/seconds/Hz, it is measured. The cell throughput will be calculated in bits per second if you multiply it by the bandwidth. The implementation of antenna arrays comprising numerous active elements at base stations, coupled with the utilization of coherent transceiver processing, presents a promising approach for enhancing the spectral efficiency (SE) of cellular networks through the deployment of 5G wireless cellular orientation.

$$\text{Spectral efficiency } \eta_S = B/\Delta v_{ch} \quad (8)$$

where B is the single-channel bit rate and Δv_{ch} is the channel spacing

Throughput

The throughput of a network or communication transmit is the pace at which data is successfully transferred through them.

$$Throughput = total\ number\ of\ packets\ sent\ /time \quad (9)$$

BER

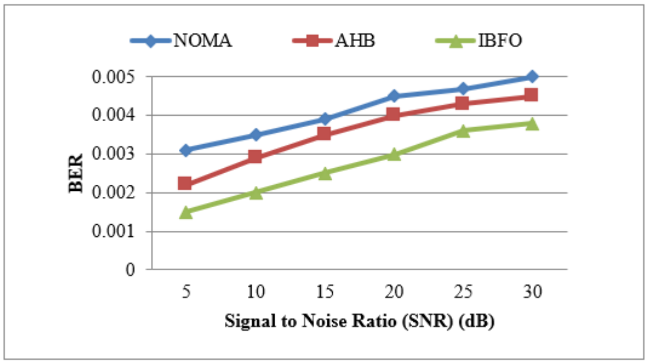


Figure 5: BER

From the Fig 5, it can be observed that the comparison of BER using existing NOMA, AHB and proposed IBFO algorithms. In the x-axis SNR is taken and, in the y-axis, BER metric is taken. Fig 5 shows that the existing methods provide higher BER whereas the proposed IBFO algorithm provides lower BER. The proposed IBFO algorithm provides the optimum transmit antenna technique in terms of lower BER performance. From the result, it concluded that the proposed framework improves that the optimal antenna selection and sub channel allocation performance rather than the existing algorithms

Sum Rate

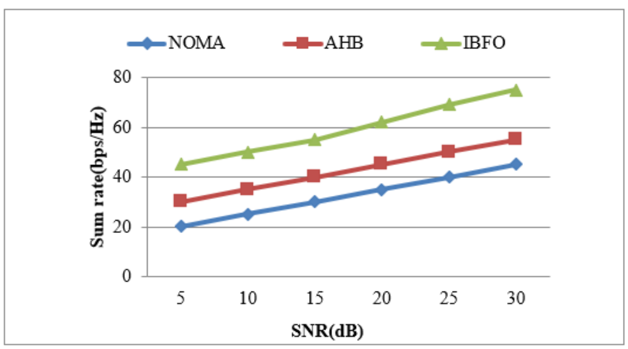


Figure 6: Sum Rate

From the above Fig 6, it can observe that the comparison of existing NOMA, AHB and proposed IBFO algorithms in terms of sum rate. In x axis we plot the SNR and in y axis the sum rate values are plotted. In existing scenario, the sum rate values are lower by using NOMA, AHB methods. In proposed system, the sum rate value is increased significantly by using the proposed IBFO algorithm. It is used to achieve sum rate of the uplink multiuser large-scale MIMO mmWave system for the number of antennas. The objective of IBFO is to identify the ideal number of RF chains that are activated in order to optimize the sum rate. It is imperative to employ a suitable methodology for antenna selection while simultaneously determining the optimal quantity of active RF chains. To achieve the maximum average sum rate while maintaining equal received power, the optimal number of activated RF chains is determined through analytical methods. With regard to the system sum rate, the least favourable set of RF chains is subsequently selected for activation. It enables balancing of the transmitted power and RF chain power consumption. Thus, the proposed IBFO shows that efficient and optimal antenna selection performance in MIMO mmWave system.

Energy Consumption

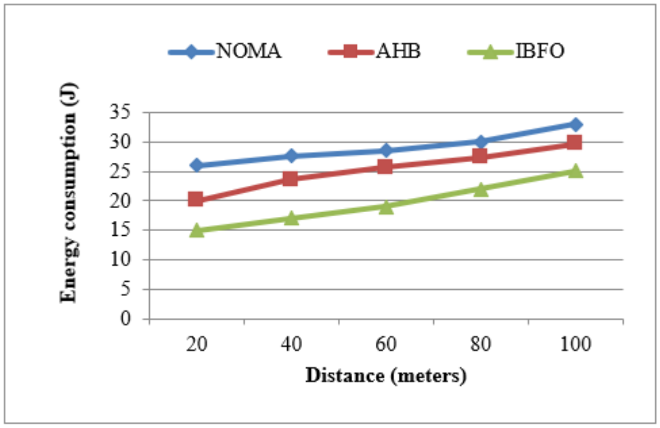


Figure 7: Energy Consumption

From the Fig 7, energy usage is compared using NOMA, AHB, and suggested IBFO algorithms. Distance and energy consumption are measured on the x- and y-axes, respectively. During the antenna selection process, consumption of energy is significantly minimized with the help of proposed IBFO algorithm over the MIMO mmWave systems. IBFO is used to improve the energy utilization which is focused to build sub channel effectively. It shows that the existing methods provide higher energy consumption whereas the proposed IBFO provides lower energy consumption.

Spectral Efficiency

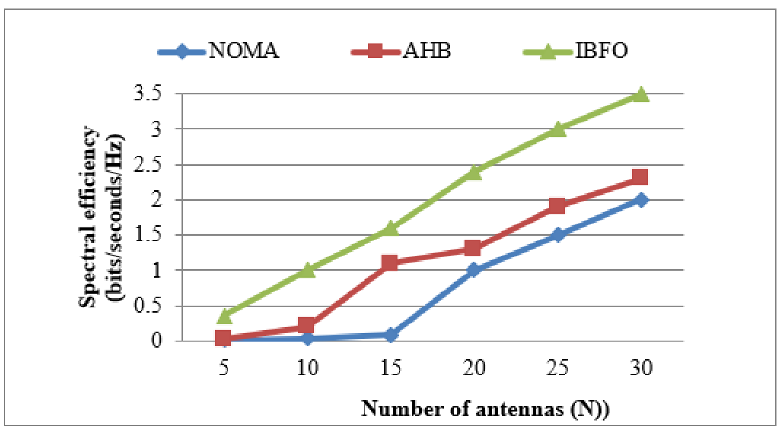


Figure 8: Spectral Effectiveness

The comparison of the proposed IBFO algorithm with the current NOMA, AHB, and spectral efficiency metrics is shown in Fig. 8. Antenna count and spectral efficiency metrics are shown on the x and y-axis, respectively. To find the best section of antennas, the suggested IBFO algorithm is applied. Increasing spectral efficiency is a very desired way to increase cell throughput. Additionally, space division multiple access on MIMO mm Wave systems are utilized to concurrently serve several user terminals in the cell using the same bandwidth, improving spectral efficiency. It shows that the existing NOMA, AHB methods provide lower spectral efficiency whereas the proposed IBFO provides higher spectral efficiency

Throughput

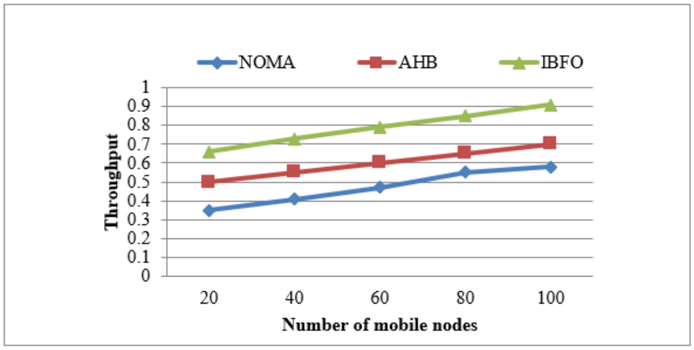


Figure 9: Comparison of Throughput

Fig 9 illustrates the comparison between the existing NOMA, AHB and proposed IBFO methods for the throughput metric. Nodes are counted on the x-axis, while throughput is measured on the y-axis. The proposed IBFO method is used to determine and select the best antennas effectively in wireless cellular network. This helps to accurately gather and transmit the data in different mobile node without any information loss. It shows that the existing IBFO methods provide lower throughput whereas the proposed IBFO provides higher throughput

5 Conclusion

In this work, proposed IBFO algorithm is proposed for optimizing the antenna selection and sub channel allocation over MIMO mmWave wireless cellular orientations. IBFO model is suggested in order to enhance the distribution of transmit power in wireless communication. A power allocation strategy based on antenna selection and sub-channel allocation is explored for transmission using MIMO mm Wave technology. In the proposed model, the transmit power determines the channel function and the necessary BER values. Optimal transmit power distribution and antenna choice are the main issues that need to be addressed. The suggested IBFO algorithm is used to resolve this issue with an appropriate antenna and efficient power distribution. Using the suggested IBFO technique, the improved objective value for the ideal transmit power is obtained. This method is tested, and it is discovered to give a better sum rate, throughput, lower BER, less energy use, and improved spectrum efficiency. In future work, can be aim to analyze the performance of the proposed framework in MIMO-IoT network. Also, hybrid swarm optimization can be developed for dealing with computational complexity issues prominently

References

[1] 5G NR Physical Channels and Modulation, document 3GPP TS 138 211, Version 15.3.0, Release 15, 2018.

[2] Akin, O., Gulmez, U.C., Sazak, O., Yagmur, O.U., & Angin, P. (2022). Green Slice: An Energy-Efficient Secure Network Slicing Framework. *Journal of Internet Services and Information Security (JISIS)*, *12*(1), 57-71.

[3] Ali, A., De Carvalho, E., & Heath, R.W. (2019). Linear receivers in non-stationary massive MIMO channels with visibility regions. *IEEE Wireless Communications Letters*, *8*(3), 885-888.

[4] Arora, S., & Singh, S. (2019). Butterfly optimization algorithm: a novel approach for global optimization. *Soft Computing*, *23*, 715-734.

[5] Cheng, Y., Li, K.H., Teh, K.C., & Luo, S. (2018). Joint user pairing and subchannel allocation for multisubchannel multiuser nonorthogonal multiple access systems. *IEEE Transactions on Vehicular Technology*, *67*(9), 8238-8248.

[6] De Carvalho, E., Ali, A., Amiri, A., Angjelichinoski, M., & Heath, R.W. (2020). Non-stationarities in extra-large-scale massive MIMO. *IEEE Wireless Communications*, *27*(4), 74-80.

[7] Eskandari, M., Doost-Hoseini, A.M., Jung, J., & Lee, I. (2018). Antenna selection and power allocation for energy efficient MIMO systems. *Journal of communications and networks*, *20*(6), 546-553.

[8] Gao, H., Su, Y., Zhang, S., Hou, Y., & Jo, M. (2021). Joint antenna selection and power allocation for secure co-time co-frequency full-duplex massive MIMO systems. *IEEE Transactions on Vehicular Technology*, *70*(1), 655-665.

[9] Hu, B.B., Liu, Y.A., Gang, X.I.E., Gao, J.C., & Yang, Y.L. (2014). Energy efficiency of massive MIMO wireless communication systems with antenna selection. *The Journal of China Universities of Posts and Telecommunications*, *21*(6), 1-8.

[10] Ioushua, S.S., & Eldar, Y.C. (2019). A family of hybrid analog–digital beamforming methods for massive MIMO systems. *IEEE Transactions on Signal Processing*, *67*(12), 3243-3257.

[11] Khalid, S., Mehmood, R., Abbas, W.B., Khalid, F., & Naeem, M. (2020). Joint transmit antenna selection and precoding for millimeter wave massive MIMO systems. *Physical Communication*, *42*.

[12] Larsson, E.G., Edfors, O., Tufvesson, F., & Marzetta, T.L. (2014). Massive MIMO for next generation wireless systems. *IEEE communications magazine*, *52*(2), 186-195.

[13] Lavdas, S., Gkonis, P.K., Zinonos, Z., Trakadas, P., & Sarakis, L. (2021). An adaptive hybrid beamforming approach for 5G-MIMO mmWave wireless cellular networks. *IEEE Access*, *9*, 127767-127778.

[14] Marinello, J.C., Abrão, T., Amiri, A., De Carvalho, E., & Popovski, P. (2020). Antenna selection for improving energy efficiency in XL-MIMO systems. *IEEE Transactions on Vehicular Technology*, *69*(11), 13305-13318.

[15] Ngo, H.Q., Larsson, E.G., & Marzetta, T.L. (2013). Energy and spectral efficiency of very large multiuser MIMO systems. *IEEE Transactions on Communications*, *61*(4), 1436-1449.

[16] Nomikos, N., Michailidis, E.T., Trakadas, P., Vouyioukas, D., Zahariadis, T., & Krikidis, I. (2019). Flex-NOMA: exploiting buffer-aided relay selection for massive connectivity in the 5G uplink. *IEEE Access*, *7*, 88743-88755.

[17] Phyo, Z.C., & Taparugssanagorn, A. (2016). Hybrid analog-digital downlink beamforming for massive MIMO system with uniform and non-uniform linear arrays. *In IEEE 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 1-6.

[18] Rawat, D.B., White, T., Parwez, M.S., Bajracharya, C., & Song, M. (2017). Evaluating secrecy outage of physical layer security in large-scale MIMO wireless communications for cyber-physical systems. *IEEE Internet of Things Journal*, *4*(6), 1987-1993.

[19] Tejera, P., Utschick, W., Bauch, G., & Nossek, J.A. (2006). Subchannel allocation in multiuser multiple-input–multiple-output systems. *IEEE Transactions on Information Theory*, *52*(10), 4721-4733.

[20] Tubishat, M., Alswaitti, M., Mirjalili, S., Al-Garadi, M.A., & Rana, T.A. (2020). Dynamic butterfly optimization algorithm for feature selection. *IEEE Access*, *8*, 194303-194314.

[21] Xu, D., Chen, X., Wu, C., Zhang, S., Xu, S., & Cao, S. (2019). Energy-efficient subchannel and power allocation for HetNets based on convolutional neural network. *In IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*, 1-5.

[22] Zhang, J., Yu, X., & Letaief, K.B. (2019). Hybrid beamforming for 5G and beyond millimeter-wave systems: A holistic view. *IEEE Open Journal of the Communications Society*, *1*, 77-91.

Authors Biography

Dra. Isabel Menacho Vargas
Doctor in Education Administration and Public Management and Governance. With a Master's degree in Evaluation of Educational Quality. Professor at undergraduate and postgraduate courses at the Universidad Nacional Mayor de San Marcos. Dedicated to intellectual property and research.

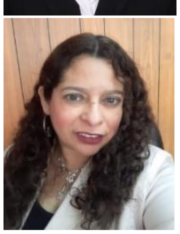
Dr. Carlos Luy-Montejo
University professor and researcher, Doctor of Education and University teaching from San Marcos National University, Master of Religious Sciences and Research and Master of Theology from the University of Wuerzburg-Germany. Research specialist, with extensive national and international experience in Information Technology, Theology, Philosophy and Humanities. Speaker at various international conferences. He is Head of the Research Unit of the Faculty of Education of the Sedes Sapientae Catholic University and a recognized methodologist at the Private University of the North.

Dra. Lourdes Ivonne Del Carmen Alcaide-Aranda
Educator University professor with Post-Doctorate in Research Methodology, Socioformation and Human Development CIFE-Mexico, with two doctorates in educational evaluation at the Pontifical Catholic University Chile-international scholarship and at the Pontifical Catholic University Perú-PUCP. Masters in education management PUCP-CIUF international scholarship. Consultant MINEDU-PESEM and SINEACE responsible for validation of the Quality Model for Institutional Accreditation of Universities

Dra. Doris Isabel Goicochea Parks
Educator with Post Doctorate in Epistemology and Research Universidad Católica Santa María Arequipa Peru, Doctorate in Administration Universidad Inca Garcilaso de la Vega, Doctor@ Strategic Planning and Economic Development University of Seville Spain, Master in Labor Administration and Industrial Relations Universidad Inca Garcilaso, Past Dean Jorge Basadre University, Member CIDI International Organization. Has vast experience in the field of networking technology.

Dra. Yoni Magali Maita Cruz
Doctoral student in public management and governance. Master's degree in health services management. Experience in Health care technology. Professor at the Faculty of Human Medicine of the Universidad Nacional Mayor de San Marcos

Dra. Jessica Paola Palacios Garay
University professor, professor in university teaching and PhD in education from the Federico Villarreal National University. She has a master's degree in research, university teaching and educational psychology integrated in communication. She works as a full-time research professor at the School of Education of the National University of San Marcos.



Dra. Aracelli del Carmen Gonzales-Sánchez
Doctor in Education, Master in Teaching and Educational Management; Bachelor in History, with a specialization in Research; specialization in journal editors at the University of Panama; Diploma in Management and Management of Publications by Sypal of the Andrés Bello University (Venezuela). Master's Degree in Teaching and Development of Competencies from CIFE (Mexico). She has a Post-doctorate in Didactics of Scientific Research (INICC-Peru).