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Intelligent Antenna Selection For Energy-Efficient MIMO Communications Using Distribution-Based Chicken Swarm Optimization

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Abstract
In recent years, the integration of energy harvesting techniques with large-scale multiple antenna systems has emerged as an effective approach to improve energy efficiency by utilizing renewable energy sources and reducing transmission power per user and antenna. Multiple Input Multiple Output (MIMO) systems employ multiple antenna elements at both the transmitter and receiver to enhance communication performance. However, the effectiveness of frequency-selective systems largely depends on how power is distributed across different frequency bands. Existing approaches often fall short in achieving optimal antenna selection while maintaining high energy efficiency in MIMO systems. To address this limitation, this work proposes a Distribution based Chicken Swarm Optimization (DCSO) algorithm for antenna selection. The proposed method optimizes transmit power, selection of active antennas, and antenna configurations at both the transmitter and receiver to improve overall system efficiency. By performing an extensive search process, the algorithm identifies the most suitable solution. Additionally, the proposed approach supports higher data rates and ensures better Quality of Service (QoS) for wireless communication. Considering challenges such as limited resources, fading channels, and user interference, the system focuses on improving spectral efficiency and reliability. The optimization framework incorporates sub-channel allocation, MIMO configuration, and bandwidth distribution to meet real-time application requirements. Experimental results demonstrate that the proposed DCSO-based model achieves superior performance compared to existing methods, including reduced Bit Error Rate (BER), lower energy consumption, and improved sum rate and spectral efficiency. This confirms that the approach provides an effective power allocation strategy by selecting optimal antenna elements based on the best fitness values.

Key words: Antenna selection, Distribution based Chicken Swarm Optimization (DCSO) algorithm, Multiple Input-Multiple Output (MIMO), energy efficiency

1. Introduction

Massive MIMO systems are essential for 5G networks to boost spectral and energy efficiency [1]. Extra-large scale massive MIMO (XL-MIMO) is a novel antenna array that can fit into gigantic structures like stadiums or retail malls [2]. The XLMIMO system, a promising and modern technology, is a leading candidate for sixth-generation (6G) and beyond technologies. Nevertheless, the technology is still in its infancy and needs more advanced approaches to evolve.

Because to the XL-MIMO system's huge antenna array, consistent long-term fading coefficients between a user and every antenna are not valid [3] and the many types of spatial non-stationarities that emerge there. The XL-MIMO scenario and the standard massive MIMO system model that is assumed in the majority of the massive MIMO literature vary primarily in this way. A very wide array's various sections are demonstrated in [4] by experimental measurements to have varied propagation pathways, and in certain situations, the terminals may only be able to view a small region of the array (VR). The non-stationarity characteristics of this novel situation are also discussed in terms of how they alter numerous critical design aspects. A MIMO aerial is seen in Fig. 1.

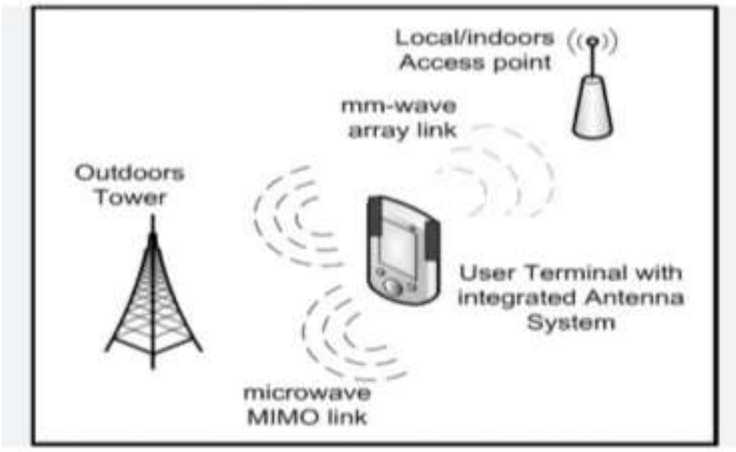

Fig 1 Example of MIMO antenna

One possible method to satisfy the demands of extremely high spectral efficiency (SE) and energy efficiency (EE) for the next wireless networks is massive MIMO [5]. Simple linear precoders and detectors in massive MIMO systems are asymptotically optimal in capacity as the number of BS antennas approaches infinity. It is a difficult problem for the future wireless networks to enhance both the energy efficiency and spectral efficiency by about the same amount as the data throughput. Massive MIMO may increase energy efficiency by three orders of magnitude without taking into account the circuit power usage.

Generally, antenna selection technology, the optimal solution is one which links the best antennas to a few radio frequency circuits. On the assumption that the aerial's spatial range satisfies signal multiplexing requirements and based on the selected MIMO system's maximum capacity criteria, the article uses a low computational complexity and high performance joint transmitting and receiving aerial selection approach. We use a simpler channels capacities statement by continually iterating to eliminate a row and a column of the corresponding decrement channel matrix, which is to eliminate a pair of sending and receiver antennae, starting with the conventional capacity formula and the complete MIMO channel matrix.

The main aim of this research work is optimal antenna selection in MIMO systems. There are several research and methodologies introduced but the energy consumption is not achieved significantly. To overcome the abovementioned issues, in this research, to boost overall network efficiency, the distribution-based Chicken Swarm Optimization (DCSO) method is presented. The main contribution of this research is construction of system model, energy model, antenna selection and sub channel allocation. Better results are produced using the suggested technique using effective algorithms for industrial mobile devices

As follows are the remaining components of the work: In Section 2, there is a quick summary of some of the studies on aerial selection. Section 3 of the proposal contains specifics regarding the DCSO algorithm technique. Section 4 presents the experiment findings and a description of the effectiveness evaluation. Lastly, Section 5 summarises the findings.

2. Related work

In [6], Zhuang et al (2020) presented an efficient way to simplify the MIMO systems' complicated complexity. In this document, a reducing joint transducing and having received AS joint transmissions and having received antenna selection method is developed to find a good compromise between the capacity and the computational complexity for antenna selection scheme. This innovative AS method maximises MIMO system capacity. The novel combined transmission and received aerial selection approach achieves sub-optimal efficiency, according to the curves of computer simulations on capacitys indication. However, compared to the ESAS method, its complexity is far lower. A big chosen number is suitable for the new combined transmission and received aerial selection method. Moreover, a certain diversity gain may be provided by the spatial multiplexing of a multi-antenna system, which has significant benefits for bit error rate.

In [7], Hu et al (2014) showed that MIMO had considerable energy and spectrum efficiency advantages over traditional MIMO technology, needing tens or hundreds of base station antennas supporting a far fewer number of terminals. Radio frequency (RF) chains must be large in order to accommodate big antennas. Massive MIMO wireless communication systems need aerial choice at both the sending end and received end because to the significant power usage and expensive cost of RF links. A convex optimization-based energy-efficient aerial choosing strategy is applied for Massive MIMO wireless communication systems. If the cell's channel capacity is over a particular level, the number of transmit antennas, subset of transmit antennas, and servable mobile terminals (MTs) are adjusted for optimal energy efficiency. A detailed proof is given for the joint optimisation issue. Analysis and numerical simulations are used to verify the method. When compared to no aerial selecting, a good energy efficient performance boost is realised.

In [8], Eskandari et al (2018) developed a fresh approach to the point-to-point multiple-input multiple-output (MIMO) spatial multiplexing systems' EE maximisation and power allocation problems. An optimum closed-form solution shows how system parameters like circuit power and channel conditions affect the ideal EE, in contrast to traditional energy-efficient optimisation techniques that call for iterative numerical computations. We also use closure forms functional to set an upper limit on the optimal EE for active transmit antennas. We also use a novel antenna selection approach based on the obtained upper limit that, although being much less complicated, provides nearly the same efficiency as the optimal situation.

In [9], Zhou et al (2014) proposed a user quality of service (QoS) constrained energy-efficient aerial selection and power allocation system to optimise EE. Utilizing the characteristics of nonlinear fractional programming, an iterative offline optimisation approach is employed to resolve the non-convex EE optimisation problem. Computer simulations are used to examine and verify the links between the maximal EE, chosen aerial number, battery capacity, and EE-SE tradeoff.

In [10], Yongqiang et al (2013) in order to increase potential in wireless MIMO communication systems, it was explored the receive antenna selection problem, This may be written as an integer programming optimisation problem, but owing to the discrete binary aerial selection factor's non-convexity, cannot be addressed directly. To solve this difficulty, the Particle Swarm Optimization (PSO) technique defines the particle as the discrete binary antenna selection factor and correlates the best solution with the capabilities corresponding to the given antenna subsection indicated by the particle. PSO is a computationally efficient method. To satisfy the criterion that the number of selected antennas should remain constant, the particle components are loosened to move among [0 1], and the position of the higher elements is taken as the index of the antenna subsection to be active. Finding the worldwide optimum particle in PSO will then lead to the discovery of the best aerial subset. Numerical findings demonstrate that the PSO approach works well for the benchmark function and aerial selection.

In [11], Cheng et al (2018) In a multisubchannel multiuser nonorthogonal multiple access (NOMA) system, the challenges of joint user pairing and subchannel allocation (JUP-SA) were examined. We initially examine the uplink using JUP-SA to optimise the minimum user diversity order. The worst-performing user's outage probability restricts the system's feasible diversity order. A JUP-SA scheme that optimises the minimal diversity order is then offered after the systems downlink is taken into account. Next the simulated findings are used to generate and verify the closed-form formulation of the worst-case outage probability. The same diversity order as that of exhausting study may be achieved by both strategies in uplink and downlink NOMA systems, according to numerical findings.

In [12], Xu et al (2019) discussed Heterogeneous network (HetNet) as a possible method for coping with the surge in wireless traffic in the Fifth Generation (5G) system. In order to enhance the energy efficiency (EE) of HetNets, a combined subchannel and power allocation issue is developed. The subchannel and power distribution judgements are made using a convolutional neural network (CNN) technique instead of iterative methods. This is done by breaking the original issue into two subproblems: classifying and regress. More evidence comes from numerical data showing that the CNN requires just 6.76% of the CPU duration to attain efficiency comparable to that of the comprehensive technique.

In [13], Liu et al (2016) investigated the primary trade-off between Spectral Efficiency (SE) and Energy Efficiency (EE) for massive MIMO systems with linear precoding and transmit aerial selection, where both the amount of circuit energy used and large-scale fading are taken into consideration. SE stands for Spectral Efficiency, while EE stands for Energy Efficiency. As the EE and SE are optimised for transmit antennas and power, we structure the EE-SE tradeoff as a mixed-integer-continuous-variable multiobjective optimisation (MOO) problem. The developed EE-SE relations analyse the Pareto front for the EE-SE tradeoff. To solve the difficult MOO problem, we develop two algorithms: the normal-boundary-intersection particle swarm optimisation (NBI-PSO) and the weighted-sum PSO. The two algorithms can meet the Pareto ideal EE-SE tradeoff, according to simulation findings, and NBI-PSO offers more equally distributed solutions than WS-PSO.

In [14], Gao et al (2021) to increase the use of time-frequency resources and physical layer security, a Co-Time Co-Frequency Full Duplex (CCFD) large MIMO network was devised. In order to prevent eavesdropping from intercepting simultaneously data broadcasts from the base station and the users, this practise is known as same-frequency interference. We use a joint antenna selection and power allocation (JASPA) technique for CCFD large MIMO networks to encourage energy saving and enhance resources utilisation. In order to address two security problems, we develop optimisation methods based on JASPA that take into account the trade-off between secrecy performance and system communications efficiency. To find the best JASPA scheme, we create the quantum-inspired backtracking search algorithm (QBSA). According to simulated data, the QBSA performs better in CCFD large MIMO systems than earlier clever algorithms. A foundational piece for future study in the field of wireless communications, the JASPA scheme's usefulness is shown in a variety of communications situations.

3. Proposed methodology

In this work, optimal antenna selection is done by using Distribution based Chicken Swarm Optimization (DCSO) algorithm over MIMO systems. This work includes system model, energy model, antenna selection and sub channel allocation. Fig. 2 shows the suggested framework's overall block diagram.

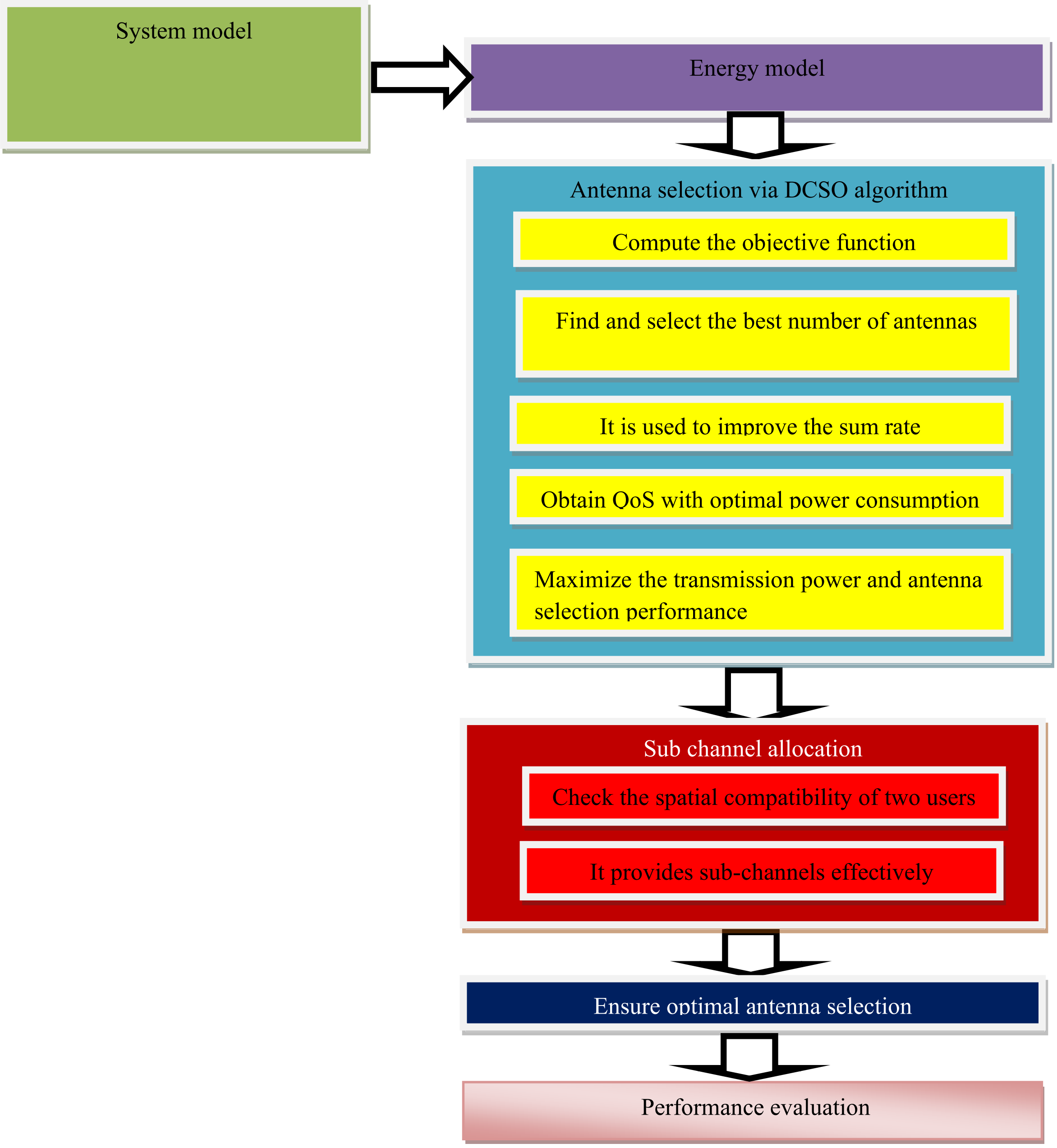

Fig 2 Block schematic of the overall planned system

3.1 System model

A multi-user massive MIMO network over a B Hz bandwidth is taken into consideration in this study. The system includes a BS with M antennas, K double antenna users, and N single antenna users. The BS and users communicate using CCFD mode. The same frequency band is used by both the BS and users. The additional Mr antennas receive information from the BS while the Mt (Mt <M) antennas emit signals. Using various antennas, the users concurrently broadcast and received data. This block of symbols is sent to the receivers within a time interval denoted by the letter "T," and the system model is represented as

$$\mathrm{Y} = \mathrm{N} + \mathrm{H} * \mathrm{X} \quad (1)$$

In this case, the received symbol matrix is denoted by Y with dimension of rxt, The sent codeword is shown as X of dimension txt, The noise matrix is shown as follows: N, and represents the Rayleigh fading channel coefficient matrix. H. Given that the collection of global channel state information (CSI) is theoretically feasible and that all channels are Rayleigh fading channels [15]. In one time period, the CSI among two nodes is unaffected; hBS_Uk $\in$ C1 $\times$ Mt is used to indicate the CSI vector from the BS's transmitting antennas to the user $\mathrm{k}\,(\mathrm{k} = 1, 2, \ldots, \mathrm{K})$, In CCFD large MIMO networks, the BS and users simultaneously transmit and collect data. Realistically, we assume poor self-interference cancellation at valid nodes.

3.2 Energy model

Each active antenna in the real systems requires its own RF chain. The standard circuit power usage model is what we use [16], where the estimated total power usage is $P_{tot} = \frac{B.P_t}{\eta} + N_t.P_{Bc} + P_{etc}$ the first term $\frac{B.P_t}{\eta}$ is the power amplifiers' power consumption and η is the efficiency of the power amplifier. $P_{Bc} = P_{DAC} + P_{mix} + P_{filt}$ shows how much power is used by the circuits connected to each active antenna at the BS. P_{etc} reflects the power consumption of the other circuit.

3.3 Antenna selection

Antenna selection in this study is carried out using the DCSO method. Each user is given an equal amount of power in order to calculate the total number of ideal antennas. Based on the power allotted, the user determines the number of antennas. The suggested technique is utilised to choose the aerial and assign the transmit power. These elements are thought to increase the systems sum rate and decrease power usage. The nodes are chosen for antenna selection based on transmit energy usage and high energy efficiency values [17]. The suggested technique also significantly reduces feedback overhead, which is essential for accomplishing high capacity and low CPU time antenna classification. The linear procedure of the base station is shown in block diagram form in Fig. 3

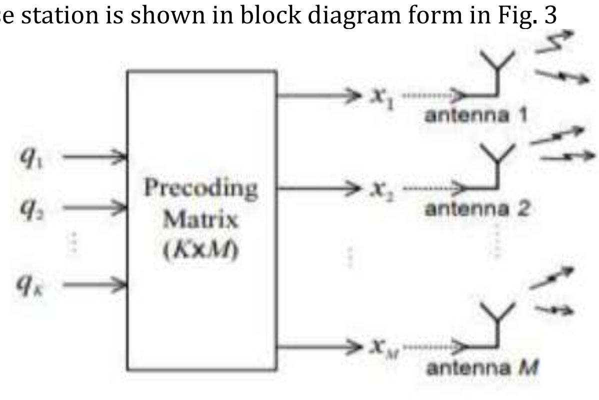

Fig 3 Block Diagram of the Base Stations Linear Process

The optimal power allocation level is calculated using the anticipated BER value. You may estimate the generalised BER value by using

$$g(\sigma1, p1) \approx p \times exp\{-q \times \sigma1 \times p1\} \quad (2)$$

Where $\sigma1 = \frac{1}{(2^m-1)\sigma^2 \sum_{n=0}^{Nr-1} |w^{(l,n)}|^2}$

The modified symbol's total number of bits is denoted by the variable m, while the constant Pl is utilized to indicate the transmit power of the lth antenna. When the transmit power is distributed uniformly throughout the domain space under consideration, the global power cannot be derived. In order to determine the best power allocation using the BER expression, the suggested DCSO method is applied.

Using a novel bio-inspired algorithm called CSO, it is possible to effectively extract the swarm intelligence of chickens to solve issues by emulating their hierarchical order and behavioural patterns, including roosters, hens, and chicks. In order to maximise classification efficiency while decreasing the amount of chosen features, CSO is used in feature selection. The programme imitates the hierarchical structure of a swarm of chickens and the actions of the chickens in each individual swarm. One rooster and several hens and chicks make up each of the groups that make up the hierarchy of a swarm of chickens. Various laws of motion apply to various types of chickens. The social lives of chickens are significantly influenced by a hierarchical structure. In a flock of chickens, the stronger chickens will rule over the less capable ones. The more subservient hens and roosters are situated towards the group's perimeter, while the more dominant hens prefer to stay close to the head roosters. The CSO algorithm's nature is shown in Fig. 4.

Fig 4 Nature of CSO algorithm

Chickens Movements

Rooster Movement: Better-fit roosters have a larger variety of locations where they may look for food.

Hen movement: To find food, hens follow the roosters in their flock. They also collected other hens excellent food while being inhibited. Dominant chickens would out compete obedient ones for food.

Chick movement: In order to get nourishment, the chicks roam about their mother.

The rules that follow describe the actions of the chickens and form the foundation of the mathematical model of CSO presented in [18]:

1) There are many groups within the flock of chickens. A dominant rooster rules each group, followed by several hens and chicks.

2) The roosters, who lead the swarm, have the greatest fitness ratings, while the chicks have the lowest. The chickens would be the other.

3) The mother-child, dominance, and swarm hierarchy will remain in a group. Only sometimes do these statuses change.

4) The virtual chickens in the swarm are separated into n groups as follows: R_n, $H_n C_n$, and M_n This, in turn, corresponds to the number of hens, chicks, roosters, and mother hens. Positions in a D-dimensional space serve as a representation of each person.

$$x_{i,j}(i \in [1,\ldots,N], j \in [1,\ldots,D]). \tag{3}$$

More priority for food availability is given to the roosters who are fitter than the roosters that are less fit. To recreate this problem, just exploit the fact that roosters with higher fitness values can hunt in more places than those with lower fitness values. The normal CSO have problem with error rate hence Gaussian distribution is introduced to avoid the error rates significantly. Then the IDCSO can be formulated below

$$x_{i,j}^{t+1} = x_{i,j}^{t} * (1 + Randn(0, \sigma^2)) \tag{4}$$

$$\sigma^2 = \begin{cases} 1, \ \ if\ f_i \leq f_k & k \epsilon [1, N], k \neq i \\ exp(\frac{(f_k - f_i)}{|f_i| + \varepsilon}, & otherwise \end{cases} \tag{5}$$

Where Randn (0, σ^2) has a mean of 0 and a standard deviation, and is Gaussian σ^2,ε Computers lowest constant prevents zero-division mistakes. k, from the group of roosters, a rooster's index is chosen at random, and f is the matching fitness value x.

The hens, on the other hand, may go in search of food with their roosters in the group. They also collected other hens excellent food while being inhibited. Dominant chickens would outperform submissive ones in feeding competitions. Following are some mathematical formulations for these occurrences.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S_1 * rand * \left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S_2 * rand * (x_{r2,j}^{t} - x_{i,j}^{t}) \quad (6)$$

$$S_1 = exp((f_i - f_{r1})/(abs(f_i) + \varepsilon) \quad (7)$$

$$S_2 = exp((f_{r2} - f_i)) \quad (8)$$

A uniform random number termed "rand" over [0, 1]. $r1\epsilon[1,..N]$ is a group member of the ith hen and an index of the rooster, while$r2\epsilon[1,..N]$ is a measure of the chicken, either a rooster or a hen, which is picked at random from the swarm $r1 \neq r2$.

Obviously,$f_i > f_{r1}, f_i > f_{r2}$, thus S2 <1< S1. In the event where S1 = 0, the ith hen would be the first to go searching for food, then the other hens. S2 is smaller and the distance between the two chickens' placements is wider the more the two hens' fitness ratings diverge from one another. This would make it harder for the hens to take the food that other birds had discovered. Since there are contests inside a group, S1 formula form is different from S2. For ease of use, the contests between the chickens in a group are used to represent how fit the chickens are in comparison to how fit the rooster is. The ith hen would look for food in its own region if S2 were to equal 0. The rooster's fitness value is distinct for the particular group [18] [19]. Hence, the closer S1 approaches 1, the closer the ith hen is to its equivalent population rooster and the lower its fitness value. In light of this, the dominant hens would be more inclined to consume the food than the subordinate hens.

In order to seek for food, the chicks roam about their mother. Here is how it is expressed

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \quad (9)$$

Where $x_{m,j}^{t}$ location of the mother of the ith chick $(m\epsilon[1,N])$. $FL\left(FL\epsilon(0,2)\right)$ is a parameter, therefore the chick would hunt for food with its mother as a result. A random choice between 0 and 2 would be made by each chick's FL, taking into account their unique variations.

By using the present ideal value, it calculates the world optimum solutions. When users are classified into sub-bands, the DCSO algorithm's effective searching capabilities may be utilised to determine the best distribution of transmit power.

Algorithm 1: DCSO

Input: a population of $n$chickens (multiple users and antennas)

Output: Best solution x_{best} (best no.of antennas selection)

1. Initialize the parameters such as R_n, $H_n C_n$, and M_n
2. Evaluate the N chickens' fitness values, t=0; (maximum transmission power)
3. While t < $Maximum$ iteration do
4. If t%G==0 then
5. Rank the chickens' fitness values and establish a hierarchal order in the swarm
6. Divide the swarm into different groups and determine the relationship between the chicks and mother hens in a group
7. End
8. For i=1 to Mantennas do
9. If i==rooster then
10. Update the solution using (4)
11. Endif
12. If i==hen then
13. Update the solution using (6)
14. Endif
15. If i==chick
16. Update the solution using (9)
17. Endif
18. Evaluate the new solution
19. If the new generated solution is better than its previous one, update it
20. End
21. End
22. Provide result as optimum power allocation with antenna allocation

Return x_{best} (optimal no. of antennas selection)

In this technique, the antennas random positions in MIMO systems are used to allocate and determine the chicks. To improve the appropriate aerial that is stated in Algorithm 1, the chicken with the greatest fitness value is modified. Determine the best hens (users) with the global best seeking food mechanism fitness value by computing the best values for all poultry (users) and applying equation (9). In the suggested method, the DCSO algorithm is used to identify antenna combinations that optimise transmission power while using a minimal number of chosen antennas. Maximizing transmission power and antenna selecting effectiveness across MIMO systems is the fitness function for the DCSO.

3.4 Sub channel allocation

The efficiency of the MIMO system is improved in this study via sub channel access. The volume and bandwidth effectiveness of the system may be further improved in MIMO systems with adaptive antenna arrays at the base and mobile stations. Adaptive antenna-array-based MIMO systems always use the largest eigenvalue subcarriers to send MIMO block symbols. For broadband MIMO wireless transmission systems, this paper examines dynamic spatial sub channel allocation with adaptable beam shaping [20]. The suggested system dynamically picks the matching optimum spatial sub channels to transmit the MIMO block symbols after selecting the eigenvalue linked to the comparatively high spatially sub channel eigenvectors to produce the beam forming weights at the mobile and base stations. Across multipath fading channels, it has been shown that the suggested system is capable of achieving superior performance than an adaptive antenna array-based MIMO system that does not use dynamic spatial sub channel allocation. As compared to typical adaptive antenna-array-based MIMO systems, the suggested system is much less prone to feedback delay in channels with rapid time-varying characteristics. On the other hand, it is somewhat more sensitive to channel estimate mistakes.

The Singular Value Decomposition (SVD) of the MIMO channel, which does not need the consecutive encoding characteristic, is equal to our zero-forcing allocation technique if all receive antennas can cooperate. Instead, our approach is equal to a Zero-Forcing with Successive Encoding Method (ZF-SE) with optimum encoding order and user option if cooperation among receive antennas is not available. In the intermediate circumstances, MIMO channels corresponding to groups of cooperative receive antennas are diagonalized [21]. We refer to our strategy as cooperative zero-forcing with subsequent encoding and subsequent allocation technique because it makes advantage of the receive antennas cooperative capabilities and successively allots subchannels to users.

There are two parameters of the block-ZF-SE technique that may be optimised with a goal of maximising sum rate. As previously mentioned, the method allocates to a particular user as many subchannels as the rank of its projected channel matrix at each stage. If, for instance, some of the subchannels are weak, this is obviously suboptimal. In such instance, these subchannels may have little effect on the total rate but may severely limit the ability of subchannels of users who have subsequently encoded data to communicate. Encoding order serves as the second parameter. Returning to the ZF-SE method, the next section proposes an algorithm that directs users with the goal of maximising the possible sum rate. We refer to this method as zero-forcing with Successive Encoding and Successive Allocation Method (ZF-SESAM) since the procedure includes the consecutive distribution of subchannels to users. This algorithm criterion for subchannel allocation, together with each step's assignment of only one subchannel to a specific user.

Multi-user MIMO processing methods in wireless communication systems require new channel allocation approaches to maximise the transmitter and receiver's spatial processing capabilities. As receiver spatial processing adds another element to the typical channel allocation problem, finding the best solution for a given group of users at an acceptable computational cost is difficult. Assuming full channel state information at the transmitter of a Gaussian broadcast channel, methods are investigated for allocating subchannels in the frequency and space domain to each receiver to maximise channel rate. For the newly found general sum capacity maximising approach, each vector channel is converted into a collection of scalar channels. In this study, a two-step heuristic is suggested. The first step computes a geographic compatibility metric for two users. After maximising the total of the suitability metrics across all groups, the users are divided into shared channels in the next stage. Moreover, it offers the option for a single user's sub-channels 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

The numerical findings are explored using the theoretical principles with a limited number of antennas and secondary users. Consider g1,1, g1,2,..., g1,K as being mutually independent and unit-mean. The power gain matrix g1 for the Rayleigh fading may be thought of as exponentially distributed. The circularly symmetric Gaussian model is considered to have a zero mean, unit variance, and Rk as the representation of the channel matrix elements. The identity matrix of the covariance noise matrix is taken for granted. There are two receiving antennas and five broadcasting antennas. With relation to the noise power, the SU power is expressed in dB, and the overall transmission power is expressed by the letter "p". Each scenario receives an average of 10,000 test runs. Performance parameters including energy consumption, bit error rate (BER), execution time, and spectrum efficiency are validated using the current NBI-PSO [13], QBSA [14], and suggested DCSO algorithms.

Bit Error Rate (BER)

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

$$BER=\frac{number\ of\ bits\ received\ in\ eror}{tota\ lnumber\ of\ bits\ transferred} \quad (10)$$

Sum Rate

Sum rate is just the sum of all rates of communications happening in a network. The statement is pretty self-evident: The more time your nodes can communicate, the more data they can transfer

Energy consumption

The huge MIMO scheme's most important criteria are Energy Efficiency (EE). Energy efficiency trade-offs for MIMO uplink transmission must be calculated by balancing the quantity of base station antennas with the quantity of users that are actively using the network. An antenna efficiency is measured as a ratio between the power applied to it and the power it radiates. A high efficiency aerial radiates away the majority of the electricity it receives at its input.

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. By installing antenna arrays at base stations with hundreds or thousands of functional components and using coherent transceiver processing, massive MIMO is a possible method for improving the spectral efficiency (SE) of cellular networks.

Spectral efficiency $\eta_S = B/\Delta v_{ch}$ (11)

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

BER

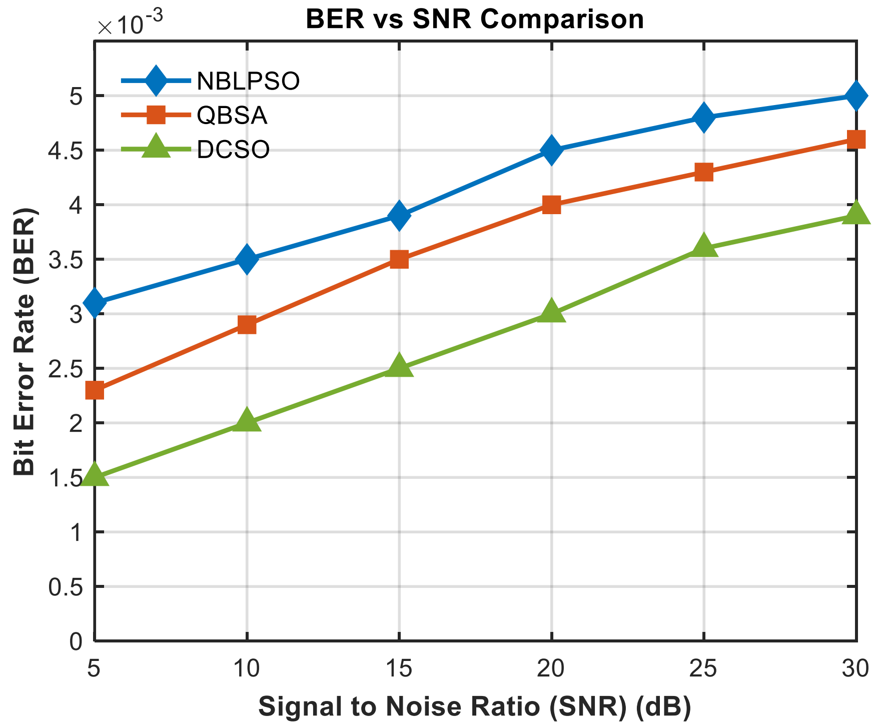

Fig 5 BER

From the Fig 5, it can be observed that the comparison of BER using existing NBI-PSO, QBSA and proposed DCSO 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 DCSI algorithm provides lower BER. The proposed DCSO 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

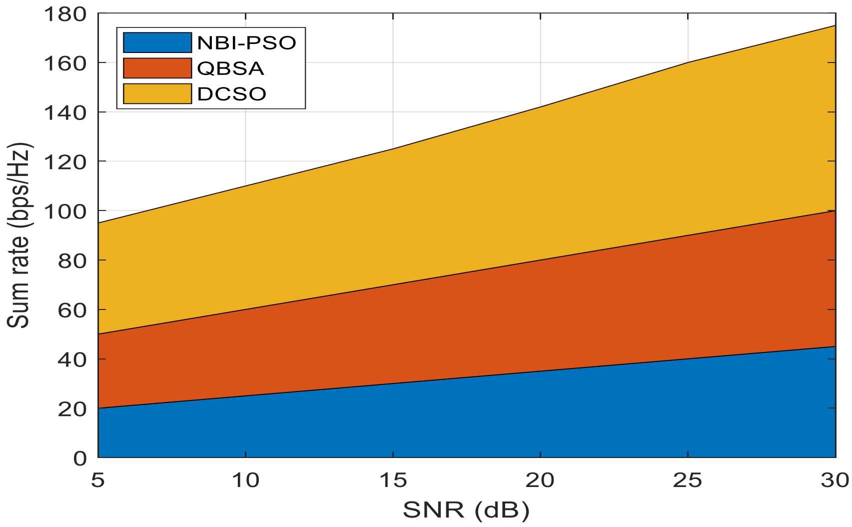

Fig 6 Sum rate

From the above Fig 6, it can observe that the comparison of existing NBI-PSO, QBSA and proposed DCSO 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 NBI-PSO, QBSA methods. In proposed system, the sum rate value is increased significantly by using the proposed DCSO algorithm. In order to maximise the uplink multiuser large-scale MIMO system's sum rate for the number of antennas, this technique is applied. Finding the right number of active RF chains to optimise the sum-rate is the main goal of DCSO. An appropriate aerial selection approach must be used in conjunction with computing the ideal number of active RF chains. In order to optimise the average sum-rate under received equal power, the ideal number of RF chains to activate is determined analytically. In relation to the system sum-rate, it then chooses the least desirable set of RF chains to activate. It makes it possible to balance the amount of power transferred and the amount of power used at the RF links. As a result, the suggested DCSO demonstrates that the performance of aerial selection in a MIMO system is efficient and optimum.

Energy consumption

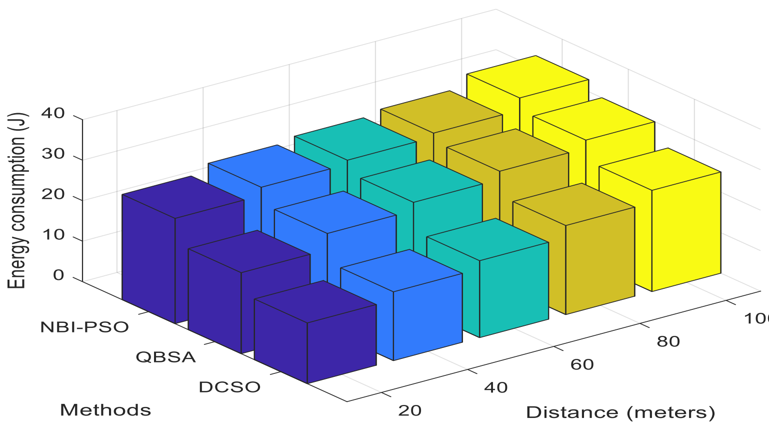

Fig 7 Energy consumption

It is clear from Fig. 7 that the new DCSO algorithm and the current NBI-PSO, QBSA, and other algorithms were compared for energy usage. The x-axis is used to measure distance, while the y-axis is used to measure energy usage. During the antenna selection process, consumption of energy is significantly minimized with the help of proposed DCSO algorithm over the MIMO systems. DCSO 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 DCSO provides lower energy consumption

Spectral efficiency

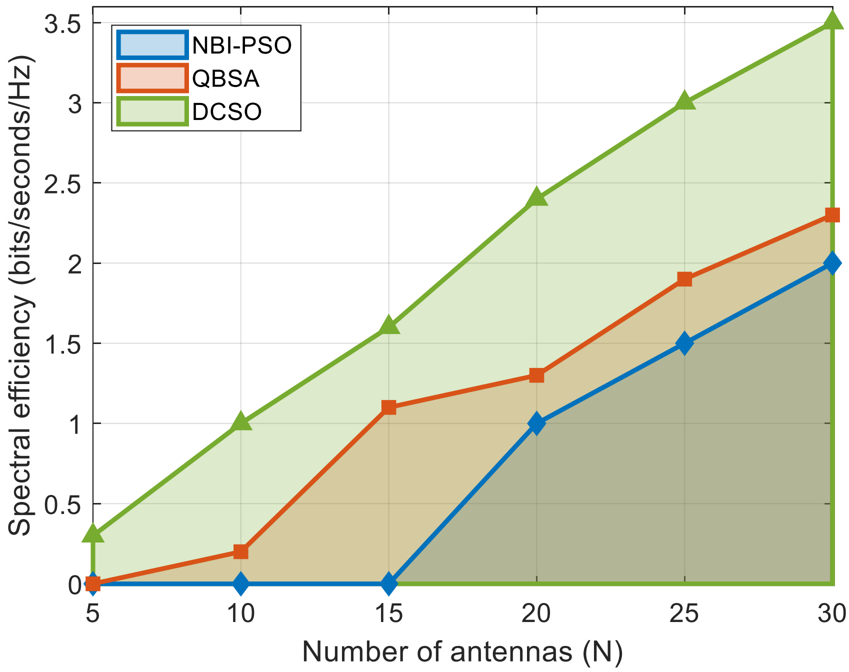

Fig 8 Spectral efficiency

Fig 8 illustrates the comparison between the existing NBI-PSO, QBSA and proposed DCSO algorithms for the spectral efficiency metric. In the x-axis number of antennas is taken and in the y-axis spectral efficiency metric is taken. The proposed DCSO algorithm is used to determine the better section of antennas. It is extremely desired to boost spectral efficiency in order to increase cell throughput. With the use of space division multiple access on MIMO systems, it is also utilised to increase spectral efficiency by concurrently serving several user terminals in the cell over the same bandwidth. It shows that the existing NBI-PSO, QBSA methods provide lower spectral efficiency whereas the proposed DCSO provides higher spectral efficiency

5. Conclusion

In this work, proposed DCSO algorithm is proposed for optimizing the antenna selection and sub channel allocation over MIMO systems. A DCSO model is suggested in order to enhance the distribution of transmit power in wireless communication. An antenna selection and sub channel allocation-based power allocation strategy for MIMO-based transmission is explored. In the proposed model, the transmit power determines the channel function and the necessary BER values. Fixing the ideal transmit power distribution and aerial choice is the main issue. The suggested DCSI method, together with an appropriate aerial and optimum power distribution, resolves this issue. Using the suggested DCSO technique, the improved objective value for the best transmit power is obtained. Better sum rate, lower BER, less energy consumption, and more spectrum efficiency are all delivered by this approach, which has been confirmed. 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

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