Chicken Swarm Optimization Based Optimal Channel Allocation in Massive MIMO

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Abstract

Energy efficiency (EE) plays a significant role in the progress towards the Fifth-generation (5G) wireless communication networks. Massive multiple-input multiple-output (MIMO) is a viable concept for the 5G networks due to the greater SE and EE. In this work, a Channel Selection (CS) scheme is proposed by selecting the optimal channel using the Chicken Swarm Optimization (CSO) algorithm. A massive MIMO model is implemented by considering the SE and EE. The main objective is to optimize the beam-forming vectors and power allocation for all the users. The multi-objective function can be defined to develop an effective and robust design with balanced SE and EE. The objective function for generating the optimal beam forming vectors is satisfying the signal to interference-plus-noise ratio (SINR) constraints. Based on the channel characteristics, the CSO Algorithm is used to produce the beam-forming vectors and power distribution. A projection matrix with a channel estimating framework is created once the channel state information is predicted. The selection of the index sets in the iteration process provides the optimized channel. Data transmission is performed through the optimal channel. According to the comparison analysis, the suggested CS scheme offers superior SE and EE to the existing CS schemes.

Keywords

Chicken swarm optimization (CSO) · Energy efficiency (EE) · Massive multiple-input multiple-output (MIMO) · Spectral efficiency (SE)

1 Introduction

Based on the rising demand for multimedia applications, there has been a lot of attention paid to enhancing the SE and EE of wireless communication systems in the last ten years. Massive MIMO is the ideal paradigm for 5G networks due to its high SE [1] and EE [2, 3]. The primary goal of Massive MIMO is to increase throughput and SE by outfitting Base Stations (BSs) with numerous antenna components at the transmitter and receiver and
combining them together. Additionally, it offers new spatial degrees of freedom to simultaneously serve many user terminals on the same time–frequency channel. The communication performance in terms of data rate and connection reliability improves concurrently with the increase in antennas [4–7].

The SE is significantly improved when many antennas are used to accommodate a high number of users connected to the same radio channel, but the EE and power consumption of MIMO systems are drastically reduced [8]. Along with the expansion of the huge number of antennas deployed at the BS that are equipped with Analog to Digital Converters (ADCs) and Digital to Analog Converters (DACs), operational costs and power consumption also rise [5, 7, 9]. High-speed ADCs are either unavailable or prohibitively expensive for practical use given the enormous bandwidth and high sample rates required for the next-generation wireless communication systems [10]. For Massive MIMO systems, it is advised to use low-resolution ADC/DACs [11–14]. Due to the use of a single comparator, the absence of linear amplifiers, and automatic gain control, one-bit ADC/DACs have the lowest hardware requirements and power requirements. The advantages of using low-resolution/mixed ADCs to lower power consumption have been experimentally verified by systems in use [15–17].

The transmit power of the users is correlated with the EE value, according to a study by Ngo et al. [3]. However, the energy consumption in the actual large MIMO systems should take into account both the power used in the radio frequency circuit and the power that is emitted. In order to maximise the EE value by allocating the time and power resources, Chen et al. [18] analysed the tradeoff between the SE and EE. The proper beam-forming design reduced the SE value while enhancing the EE value [19]. It is concluded that the SE value decreased as a result of the EE value rising. Consequently, a unique method is needed to maintain the trade-off between EE and SE in massive MIMO systems.

The swarm intelligence based optimization and evolutionary algorithms are found to be effective for the optimization of the beam patterns. Previously, Genetic Algorithm (GA) [20], Particle Swarm Optimization (PSO) [21], Ant Lion Optimization (ALO) [22], Flower Pollination Algorithm (FPA) [23], hybrid Invasive Weed Optimization (IWO)/Wind Driven Optimization (WDO) [24], PSO-Gravitational Search Algorithm-Explore (PSOGSA-E) [25] and Firefly Algorithms (FA) algorithms [26] were applied for the beam pattern optimization. Improved CSO algorithm is used to determine the best channel because the previous swarm intelligence-based approaches have a low convergence rate and lack of stability. The benefits of the PSO and Differential Evolution (DE) algorithms are carried over to CSO. Due to the chickens’ varied travels between different groups, the search space is efficiently explored and a nice balance between randomness and tenacity for discovering the optimum results is obtained. The entire swarm may work together as a team to find food for a particular hierarchical order. This might be connected to the efficient extraction of chicken swarm intelligence for the optimization of the objective problems. As a result, the CSO algorithm performs well.

The fitness function is computed in the proposed work after initialising the parameters and population. The positions of hens, roosters, and chickens are updated after the best solutions are found. Once the global ideal positions have been determined, the maximum number of iterations has been attained is verified. The ideal channel output is obtained if the maximum number of iterations is reached. If not, the estimation of the fitness function is the next step in the procedure. A better balance between the SE and EE in the large MIMO system is accomplished by the optimization of the power allocation and beam forming vectors.
The major objectives of the proposed work are.

1. To develop an improved massive MIMO model with a balanced trade-off between SE and EE.
2. To construct a trade-off between SE and EE by optimizing the power allocation and beam-forming vectors.

The structure of the paper is organized as follows: Sect. 2 provides a brief review of the existing research works related to the massive MIMO networks. Section 3 describes the proposed work including system model, objective model, optimal power allocation and beam-forming vectors and CS scheme with the CSO algorithm. Section 4 discusses the comparative analysis of the proposed CS scheme with the existing CS algorithm and CS with mixture of Gaussian cluster model, and Sect. 5 concludes the work summarizing the key ideas.

2 Literature Review

Relay networks also need higher EE. Analysis can be done for the relay networks to reduce the power consumption. One of the literature which considers the full-duplex relay with a large number of antennas to reduce the power consumption is dealt by Zhang et al. [15, 16] to exchange information using multiple pairs of amplify and forward two-way relay channels. Based on the different receivers at the relay, four power-scaling techniques were developed. When the number of relay antennas hits infinity, the asymptotic SE and EE for the suggested designs were quantified. The enormous number of antennas also eliminated inter-pair and inter-user interferences. By lowering the transmission power applied to the relay antennas, the loop interference could be lessened. The proposed power-scaling strategies successfully balanced performance between the SE and EE.

EE can be achieved by many ways in massive MIMO systems. One of that is the one bit ADC in the RF chain. Some of the literatures have considered mixed ADC and low resolution ADCs. Li et al. [27] investigated the channel estimation issue and identified the feasible uplink rates. For the massive MIMO system with built-in one-bit ADCs, the closed-form equation for the lower bound of the feasible uplink rate was constructed using a straightforward and comprehensible expression for the Linear Minimum Mean-Square-Error (LMMSE) channel estimator. MRC and ZF channel estimators were also analysed. They proved that the suggested estimator overcome the near maximum likelihood estimator, according to their experimental results.

He et al. [28] created a flexible Device-to-Device (D2D) power management technique. D2D system is another network where the EE is required. Interference is the main challenge that needs to be considered here. The authors mentioned that to effectively prevent interference between the cellular and D2D tiers, a dynamic power control method can be used. By taking into account the maximum transmission power restrictions at the cellular users and D2D transmitters, an analytical method is created to assess the SE and EE in massive MIMO networks. To provide the precise expressions for computing the SE of the cellular and D2D tier area, a manageable approach was created. Results from experiments supported the proposed approach’s effective performance.

Multi-cell approach for the massive MIMO system increases the SE in a rapid manner. Spatial modulation is a method researched by Patcharamaneepakorn et al. [29] to improve the EE. Based on the linear processing method, a poor detection algorithm was suggested.
The sum-rate performance under the channel conditions was approximated using an analysis of the chance of detecting antenna combinations. Trade-off between SE and EE has to be taken as a very big issue in 5G and beyond networks. Additionally, Patcharamaneepakorn et al. have analysed the fundamental trade-off between SE and EE was looked into. The most effective and energy-efficient transmission mode was found to be the SM scheme with a single active antenna for each user, albeit having a lower SE rate.

The SE and EE for a massive MIMO multiple-pair two-way amplify-and-forward relaying system were investigated by Yang et al. [30]. In this method, information is sent between numerous user pairs via a relay station with massive number of antennas. It was expected that the relay station used MRC/MRT and the imperfect CSI was accessible. In massive MIMO with the huge number of antennas, power scaling strategies can be applied. This strategies used in this work to scale down the transmission power at each user and relay station. Thus the asymptotic SE and EE were quantified. About a closed-form SE expression was obtained. The experimental results showed that the transmit power at each user and the relay station could be reduced while maintaining a non-vanishing SINR.

Xin et al. [31] analyzed the performance of massive MIMO systems with the pilot contamination. A closed-form approximation of the Area SE (ASE) for uplink multi-cell multi-user massive MIMO systems was derived using a uniformly distributed user location model. The area EE (AEE) in a cell was obtained by considering a practical power consumption model. The ASE and AEE results were used to investigate the parameters of massive MIMO systems.

Tan et al. [32] derived an approximated upper bound on the achievable SE and EE of massive MIMO for the hybrid analog/digital pre-coding architectures based on the phase shifters. The BS has a perfect CSI. The baseband processing was performed based on the ZF pre-coding. It was found out that the number of BS antennas, users and Signal-to-Noise Ratio (SNR) were increased with the increase in the total achievable SE. An algorithm was proposed to generate the corresponding quantized matrix and hybrid architectures were studied. The achievable SE could be improved by increasing the bits of the phase shifters and existence of an optimal SNR and number of antennas.

Nimmagadda [33] applied modified Grey Wolf Optimization (GWO) referred as Improved Random Vector-based GWO (IRV-GWO) and modified Lion Algorithm (LA) referred as IRV-based LA (IRV-LA), to solve the complex optimization problems for beam-forming vectors and power allocation. This achieved better SE-EE tradeoff in massive MIMO technology.

A new architecture for a huge MIMO system was put forth by Schmidt et al. [34] by merging a Tone-Reservation (TR) based Peak-to-Average Power Ratio (PAPR) reduction algorithm. The goal of this endeavour was to develop highly accurate beam-steering capabilities. In order for the Power Amplifier (PA) to run at the same Input Back-Off (IBO) and produce a greater EE, it is necessary to maintain the weights allocated to each antenna. One can get a high SE by utilising a huge MIMO feature like beamforming. It was suggested that the signals sent to the antennas in the discrete time domain be given progressive time delays as part of the Beam Forming (BF) implementation. While retaining the low PAPR of the broadcast signals, good BF performance was attained.

The effect of signal detection algorithms on the energy efficiency (EE) of uplink MIMO systems with low-resolution ADCs was investigated by Liu et al. [35]. In this work it was preassumed that all users transmit data at the same rate. The optimal power allocation and analytical approximations for ZF and ZF Successive Interference Cancellation (ZF-SIC) receivers were derived. On comparing the ZF receiver with the ZF-SIC receiver, it was observed that the same performance can be obtained with less number
of antennas in ZF-SIC receiver. When combining ZF-SIC receiver and low resolution ADCs, the overall EE for massive MIMO systems was enhanced.

In the conventional MIMO system, regular pilot was utilized. For the purpose of transmission, it used different symbols for the data and the pilot. The superimposed pilots, which overlay the data and pilot symbols for transmission, were proposed by Ragunathan and Perumal [36]. The proposed pilot reduced pilot contamination while allowing the use of pilot symbols for a longer period of time. Pre-coding systems like MRC and ZF were employed to evaluate the pilots’ performance. To enhance performance, the pre-coding system was combined with the antenna selection algorithm. To increase EE, the antennas with the threshold level were selected. In accordance with the simulation results, the overlaid pilot using the antenna selection algorithm produced higher EE than the random pilots.

EE and total Power Transfer Efficiency (PTE) of massive MIMO systems were examined by Khan et al. [37]. Users may use the energy that has been gathered to transfer data to the BS on the uplink. Analysis of the total system performance considered the nonlinear behaviour of energy harvesters. In order to describe the PTE for wireless energy transfer, a scalable model was utilised. The wireless flow of energy and information was used to describe the EE performance. The number of BS antennas and users was used to determine the ideal BS transmission power. The EE was enhanced to a large number of antennas with the rise in antenna number and transmission power.

With the abundant increase in the contribution of SE and EE in massive MIMO technology, there are some challenges to improve the performance. Table 1 presents the disadvantages of the existing SE and EE models in massive MIMO system.

Many studies have concentrated on developing and examining the massive MIMO technology by addressing the SE and EE issues. These models, meanwhile, were only meant to focus on one parameter, either SE or EE. In order to create an efficient and reliable design with balanced SE and EE, the multi-objective function is taken into account. The high computational complexity and sluggish convergence rate of existing approaches cause problems. Consequently, channel optimization is achieved using a CSO algorithm.

The primary goal here is to optimise the beam-forming vectors and power distribution for all users in order to increase or improve the EE function. The fitness function is computed in the proposed work after initialising the parameters and population. The places of hens, roosters, and chickens are updated after the best solutions are found. Once the global ideal positions have been determined, the maximum number of iterations attained is verified. The ideal channel output is obtained if the maximum number of iterations is reached. If not, the estimation of the fitness function is the next step in the procedure.

Utilizing the pilot signal received in the sub-channel domain, the proposed channel selection system first estimates the channel before interpolating it to the frequency-spreading domain. The Channel State Information (CSI) estimation is then modified by once again despreading the channel compensated FS domain pilot. After applying equalisation in the frequency domain for each frequency point and a frequency despreading technique, the transmitted data can be rebuilt. The subsequent technique is used to estimate the channel. Following the despreading and pilot extraction processes, the estimated CSI at the pilot sub-channel site can first be extracted. This CSI is used to equalise the received samples by interpolating for each frequency point. Finally, changes are made to the CSI for the pilot subchannel. These processes are performed in an iterative manner for a predefined number of times.
3 Proposed Method

3.1 Channel Model

The uplink of a single cell multi-user massive MIMO system is taken into account in the suggested study. In a base station for the MIMO system, there are $N$ antennas. The same frequency resource is used by $M$ single-antenna users to transmit data to the BS. The channel deficiencies taint the data transmission. Due to multi-path reception and lognormal shadowing from obstacles in the transmission path, the data transmission from $M$ users to the BS experiences independent Rayleigh fading. The $N \times 1$ received signal vector at the BS is described as
\[ V = \sqrt{P_T C X + \mathcal{N}} \]  

where ‘C’ denotes the \( N \times M \) channel matrix between the ‘M’ number of single-antenna users and ‘N’ number of BS antennas, \( P_T \) represents the average transmission power of a single user in the channel, ‘X’ indicates the vector of the symbols simultaneously transmitted by ‘M’ single-antenna users and ‘\( \mathcal{N} \)’ denotes the noise vector.

As the BS antennas are located closely with each other, the large-scale fading for a single user across ‘N’ number of BS antennas is correlated. But, the small-scale facing coefficients are independent and identically distributed. It is assumed that there is a perfect correlation between the shadowing components of a single user across ‘N’ number of BS antennas. Hence, the received signals from the Mth user across ‘N’ number of BS antennas suffer identical shadowing. The channel matrix is given as

\[ C = LD^{1/2} \]  

where ‘L’ is the \( N \times M \) matrix of the small-scale fading coefficients and ‘D’ is a \( M \times M \) diagonal matrix including the large-scale fading coefficients of ‘M’ users. With the usage of a linear detector, the received signal is processed as

\[ R = A^O \gamma \]  

The vector ‘R’ represents the received signals from all the users, where \( A \) denotes the linear detector matrix depending on the channel matrix and ‘O’ is the Hermitian operator.

### 4 SINR Formulation

After applying the linear detector, the received signal vector is given as

\[ R = \sqrt{P_T A^O C X + A^O \mathcal{N}} \]  

The received signal vector is divided into two parts, to formulate the SINR of a single user. Let \( R_j \) denote the received signal and \( T_j \) indicate the transmitted symbol of the jth user. Then,

\[ R_j = \sqrt{P_T a_j^O C_j} \]

\[ T_j = \sqrt{P_T \sum_{m=1,m\neq j}^{M} a_j^O C_M X_M + a_j^O \mathcal{N}} \]  

where \( a_j \) and \( C_j \) indicate the jth columns of the linear detector matrix and channel matrix. The first term in the above equation denote the desired signal of the jth user and other terms constitute the interference from other users and noise. Without the loss of generality, unit power spectral density of noise is assumed. The SINR of the jth user can be represented as

\[ \text{SINR}_j = \frac{P_T |a_j^O C_j|^2}{\sqrt{P_T} \sum_{m=1,m\neq j}^{M} |a_j^O C_M|^2 + \|a_j^2\|} \]
5 Receiver Design

A linear receiver is designed with the Maximum Ratio Combining (MRC) receiver combined with the Coordinate Descent Method (CDM) based algorithmic framework.

In the case of perfect CSI, the $N \times M$ linear detector matrix $A$ for an MRC receiver is given by the channel matrix. The SINR of a single user for an MRC receiver is obtained as

$$SINR_{j}^{MRC} = \frac{P_{T}L_{j}^{2}}{P_{T}L_{j} \sum_{m=1, m \neq j}^{M} \|s_{j}^{m}S_{j}^{m}L_{m}\|^{2} + \|s_{j}^{m}\|^{2}L_{j}}$$

(8)

Conditioned on the small-scale fading coefficient for jth user, a new Random Variable (RV) $C_{M}$ is defined such that $C_{M} = \frac{|s_{j}^{m}S_{j}^{m}|}{\|s_{j}^{m}\|}$ is a Gaussian RV with zero mean and unit variance independent of the small-scale fading coefficient for jth user. Hence, $C_{M} \sim CN(0, 1)$. The SINR is described as

$$SINR_{j}^{MRC} = \frac{P_{T}L_{j}^{2}}{P_{T}L_{j} \sum_{m=1, m \neq j}^{M} C_{M}^{2}L_{m} + 1}$$

(9)

Now, the Probability Density Function (PDF) of the SNR is derived. In the above equation, the numerator is the SNR ‘Z’ of a single user at the BS. Hence,

$$Z = P_{T}L_{j} \sum_{I=1}^{M} |S_{I}|^{2} = P_{T}L_{j} \gamma$$

(10)

where $\gamma \sim \Delta(N, 1)$ owing to the sum of the independent and identically distributed exponential RVs each having unit mean value.

From the above equation, it is clearly evident that the SNR follows a gamma-log normal product distribution. The PDF of a gamma RV is given by

$$P_{C}(\gamma) = \frac{\gamma^{N-1} \exp(-\gamma)}{\Delta(N)}$$

(11)

where $\Delta(N) = (N - 1)!$ Since N is an integer. The distribution of a product RV, $Z = LC$ is given by

$$P_{Z}(Z) = \int_{-\infty}^{\infty} P_{L}(L)P_{C}(\frac{Z}{L}) \frac{1}{L} dL$$

(12)

Since $P_{L}$ is a constant, it is neglected in the PDF expression of gamma log normal product distribution. From the above equation, the PDF of the product of gamma and log normal RVs is given by

$$P_{Z}(Z) = \frac{\varphi_{Z}^{N-1}}{(N - 1)!\sigma_{db}^{2}\sqrt{2\pi}} \int_{0}^{\infty} \exp(-z/L) \frac{\exp\left(-\frac{(\varphi \log_{e}L - \sigma_{db}^{2})}{2\sigma_{db}^{2}}\right)}{L^{(N+1)}} dL$$

(13)

From the above equation, it is noted that the PDF of the SNR does not exist in a closed-form.
6 CDM-based Signal Detector

The CDM optimizes one variable at a time while holding the other variable fixed at their most recently updated values. Normally, the optimization coordinate is chosen cyclically. But, the CDM is efficient when the sub-problems could be solved [44].

For a given \( X_\mu = [x_1, \ldots, x_{\mu-1}, x_{\mu+1}, \ldots, x_U] \), the optimal value of \( x_\mu = A_\mu e^{j\theta_\mu} \) that minimizes \( \| Y - S_\mu^2 \| \) is given by

\[
A_\mu^* = \frac{|\varphi_\mu|}{\sum_{b=1}^{B} |O_{b\mu}|^2}
\]

\[
\theta_\mu^* = \arg(\varphi_\mu)
\]

\[
\varphi_\mu \triangleq \sum_{b=1}^{B} O_{b\mu}^* \left( Y_b - \sum_{L=1}^{U} O_{bL} A_L e^{j\theta_L} \right)
\]

The optimal update problem can be written as

\[
A_\mu^* e^{j\theta_\mu^*} = \arg \min_{b-1} \left[ Y_b - \sum_{L=1}^{U} O_{bL} A_L e^{j\theta_L} \right]^2
\]

7 CDM

CDM is an iterative procedure that performs sequential global minimization with respect to a single coordinate or multiple coordinates. At each iteration ‘M’, an index \( I_M \in \{1, 2, \ldots, n\} \) is selected and the decision vector is updated for the approximate minimization of the objective function in the \( I_M \) th coordinate [45–47]. CDM is an effective way for solving optimization of multi-variables. During each iteration CDM performs optimization and update of only one variable while assuming that there is no change in other variables. Also, there is a need to initialize all variables firstly, so that all the variables have initial values. While solving the \( \alpha \) th variable, the previous \((\alpha - 1)\) variables are all updated and the subsequent variables are initial values, so that the \( \alpha \) th variable could be solved and updated.

The optimal \( U_a \) for a given \( V_a = (U_1, \ldots, U_{a-1}, U_{a+1}, \ldots, U_N)^T \) is described as

\[
U_a = \varphi \left( \sum_{i=1, i\neq a}^{N} A_{ai} U_i \right)
\]

where \( \varphi(x) \) denotes the phase of a complex variable ‘x’, such as

\[
\varphi(x) = \begin{cases} 
1, & x = 0, \\
\frac{x}{|x|}, & x \neq 0,
\end{cases}
\]
Iterative CDM Algorithm

Input: $\hat{H}, V, \beta, K, M, N$
Step 1: $T_0 = I_{N_S}, V^{(0)} = V$
Step 2: for $i = 1$ to $K$ do
Step 3: for $n = 1$ to $N$ do
Step 4: $A = \hat{H}^H T_{n-1}^\alpha \hat{H}$
Step 5: for $\alpha = 1$ to $M$ do
Step 6: Determine $U_\alpha$
Step 7: end for
Step 8: Update $V_n = [U_1, ..., U_M]^T$
Step 9: $T_n = I_{N_S} + \beta \hat{H} V_n^{(i)} (V_n^{(i)})^H \hat{H}$
Step 10: end for
Step 11: Update $V^{(i)} = [v_1, ..., v_N]$
Step 12: end for
Step 13: $V^{\text{out}} = V^{(K)}$

It is set that the stopping criterion triggers the iterative algorithm as the number of iterations. It is assumed that the channel matrix ‘$H$’ is known at the transmitter. $H$ can be estimated by the receiver and fed back to the transmitter. Hence, the receiver should first estimate the perfect channel information, calculate the digital precoder $F_{BB}$, digital combining matrix $W_{BB}$, analog precoder $F_{RF}$ and analog combining matrix $W_{RF}$ and feed back analog and digital precoders to the transmitter [48, 49].

Combined Hybrid Precoding Algorithm by CDM

Input: $H, N_{RF}^R, N_{RF}^L, N_S$
Step 1: Construct Analog precoder and analog combining matrix with random phases
Step 2: Repeat
Step 3: $\hat{H} = W_{RF}^H H$
Step 4: Obtain analog precoder by solving the precoder and combiner design problem using iterative CDM Algorithm
Step 5: $\hat{H} = F_{RF}^H H^H$
Step 6: Obtain analog combining matrix by solving the precoder and combiner design problem using iterative CDM Algorithm
Step 7: Until a stopping criterion is achieved
Step 8: $H_e = W_{RF}^H H F_{RF}$ and its Singular Value Decomposition (SVD) is $H_e = U_e \Sigma_e V_e^H$
Step 9: $F_{BB} = V_e(:, 1: N_S), W_{BB} = U_e(:, 1: N_S)$
Step 10: $F_{BB} = \sqrt{N_S} \frac{F_{BB}}{\|F_{BB}F_{BB}^H\|^2_F}$ and $W_{BB} = \sqrt{N_S} \frac{W_{BB}}{\|W_{RF}W_{BB}\|^2_F}$
8 Proposed Flow

Figure 1 shows the flow diagram of the proposed work. The optimal power allocation, BF vector and optimization of the transmission power are implemented using the CSO algorithm. During the optimal power allocation, BF vectors are determined based on the following steps.

1. Determine the BF vector that should satisfy the SINR constraints.
   a. Check whether the computed BF vector satisfies the SINR constraints.
   b. If not, optimize the BF vector with some percentage of alterations, such that the alteration length should be equal to the length of the obtained BF vector.
   c. The objective function for generating the optimal BF vectors is satisfying the SINR constraints. The power penalty of 100 is given, if the SINR constraints are not satisfied.

Fig. 1 Flow diagram of the proposed CS scheme with CSO Algorithm
d. The iteration is stopped, once the power penalty reaches zero. The best solution is taken as the optimal BF vector.

2. The objective function for optimizing the transmission power is the maximization of the EE metric.

The solution with maximum RE metric is taken as the best transmission power. Thus, the massive MIMO system is obtained with better tradeoff between SE and EE.

Data group has to be spread over multiple frequency points, which correspond to the frequency coefficients of prototype filter \( F_p \) for \((-P + 1 \leq p \leq P - 1)\). This process is called as frequency disspreading. Frequency despreading is applied to synchronize the input data in a frequency domain, to recover the original data. This makes the input data robust to the interference. After frequency spreading, all the frequency points are transmitted to generate a single symbol.

The received signal is expressed as follows

\[
R(t) = \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} D_{x,y} H_{x,y}(t) G_{x,y}(t) + W_G(t)
\] (20)

where ‘X’ is the number of sub-channels and ‘Y’ is the number of frequency points, \( H_{x,y} \) is the transmission Channel State Information (CSI), \( G_{x,y}(t) \) is the filter of the \( x \)th sub-channel in the \( y \)th frequency point and \( W_G(t) \) denotes the white Gaussian noise. After matched filtering in the analysis filter bank, the result is represented as

\[
R_{x,y} = H_{x,y} \left( D_{x,y} + j \sum_{p \neq x,y} D_{p,q} G_{p,q} \right) + W_{G_{x,y}} = H_{x,y} (D_{x,y} + I_{x,y}) + W_{G_{x,y}}
\] (21)

If the scattered pilot sub-channel scheme is used for the estimation of CSI, the estimated CSI at the pilot location sub-channel \((x_p, y_p)\) is represented as follows [4]

\[
\hat{H}_{x_p,y_p} = \frac{R_{x_p,y_p}}{D_{x_p,y_p}} = \frac{H_{x_p,y_p} (D_{x_p,y_p} + I_{x_p,y_p}) + W_{G_{x_p,y_p}}}{D_{x_p,y_p}}
\] (22)

The transmitted data can be reconstructed after using the frequency despeading technique and the frequency domain equalisation approach for each frequency point. Subchannel CSI estimate is therefore required for each frequency point. The CSI estimation for each subchannel can be found after the interpolation operation. The CSI for each frequency point can then be found by interpolating once again between the CSI of the neighbouring subchannels.

In this case, the CSI for each subchannel at the centre frequency point must be gathered in order to interpolate additional frequency points. If the transmission channel is flat during the subchannel, the CSI estimation and the CSI at the centre frequency point are comparable. The CSI for each subchannel is consequently instantly substituted for the centre frequency point at the first CSI interpolation.

However, if the transmission CSI cannot be regarded as flat during each subchannel, it cannot be guaranteed that this CSI for each subchannel will be identical to the centre frequency point. It is necessary to alter this estimated CSI in order to improve the efficiency of the channel equalisation process. One way to assess the precision of the estimated CSI is to make a comparison between the duplicated pilot at the receiver and the sent pilot signal.
If the CSI is precisely determined for each frequency point in the pilot subchannel, the data component for the pilot subchannel is equal to the amplitude of the pilot symbol.

The channel estimation approach is put into practice using the method that follows. The estimated CSI can first be extracted at the pilot subchannel site after frequency despreading and pilot extraction. The received samples are equalized using this CSI, which is interpolated for each frequency point.

The CSI for each stage is stored in the channel store/correction block, and the CSI for each frequency point is produced by interpolating it in the time and frequency interpolator. After that, the channel equalizer adjusts the frequency of each frequency point. Then, using the pilot estimation value, the channel store/modification block executes the CSI modification [50, 51]. After that, the efficiency of the proposed CS scheme employing the CSO algorithm is evaluated.

8.1 CSO for Optimal Channel Allocation

Generally, the behavior of the chicken is based on its gender. The head roosters being a dominant one will search for the food and fight with the chickens who invade the territory. It crows louder when chickens from other groups invade their territory. The rooster will dominate the weak chickens and might call their group mates to share the food. The dominant hens remain near the roosters and submissive hens would stand at the periphery of the group in search of food. The chicks always stay around the mothers and search food over there. As a swarm, they all cooperate as a team/group to search food in a specific hierarchical order of roosters, hens and chicks.

Meng et al. [52] proposed the CSO algorithm, a novel bio-inspired algorithm that mimics the hierarchical structure and behavior of the chicken swarm. The several clusters that make up the chicken swarm are composed of the dominant head roosters, a few hens, and chicks. Once the swarm is divided into several groups, the identification of the chickens is determined using their fitness scores. One of the chickens with the highest levels of fitness would be the best rooster in the group. The least fit chickens would act more like young chickens. Others would be the hens that randomly choose which group they will reside in. Additionally, hens and chicks randomly form a mother–child attachment. The dominant, hen-chick, and hierarchical relationships will all persist in a group. The dominating rooster leads the flock of chickens when they are in quest of food, preventing the other chickens from consuming their own food. The excellent food that has already been discovered by others is allegedly stolen at random by the chickens. The young hens search for food close to their mother hens. The dominating roosters are invariably victorious in battles for food.

Let us assume that ‘\(N_R\)’, ‘\(N_H\)’, ‘\(N_C\)’ and ‘\(N_M\)’ denote the number of the roosters, hens, chicks and the mother hens in a group, respectively. The best \(N_R\) would be assumed to be the roosters, while the worst \(N_C\) ones would be the chicks. The rest are treated as hens. All ‘\(M\)’ virtual chickens represented by their positions \(X^{t}_{a,b}(a \in [1, \ldots, M], b \in [1, \ldots, S])\) at the time step ‘\(t\)’, search for the food in the ‘\(S\)’ dimensional space.

9 Chicken Movement

The roosters with the greatest fitness scores are given preference over those with the lowest scores when it comes to food access. This situation can be easily imitated in situations where roosters with higher fitness values are able to search for food in a wider
variety of sites than roosters with lower fitness values. The equation below can be used to explain this.

\[ P_{a,b}^{t+1} = P_{a,b}^t \times [1 + G(0, \sigma^2)] \]  

(23)

where

\[ \sigma^2 = \begin{cases} 1, & \text{if } F_a \leq F_I \\ \exp \left( \frac{(F_I - F_a)}{F_a + \psi} \right), & \text{otherwise} \end{cases} \]  

(25)

where \( G(0, \sigma^2) \) is the Gaussian distribution with mean 0 and standard deviation \( \sigma^2 \). \( \psi \) is used to avoid the zero division error. ‘I’ is the rooster’s index that is randomly selected from the group of roosters. ‘F’ is the fitness value of the corresponding position ‘P’.

The roosters in their flock might go food hunting with the hens. They can steal the amazing things they discover while being tormented by other hens. The dominant hens have an advantage over the submissive chickens in the feeding competition. A mathematical expression of this is given below.

\[ P_{a,b}^{t+1} = P_{a,b}^t + Q_1 \times U_R \times (P_{I_a,b}^t - P_{a,b}^t) + Q_2 \times U_R \times (P_{I_c,b}^t - P_{a,b}^t) \]  

(26)

where

\[ Q_1 = \exp \left( \frac{(F_a - F_{I_a})}{(abs(F_a) + \psi)} \right) \]  

(27)

\[ Q_2 = \exp \left( \frac{(F_{I_c} - F_a)}{abs(F_a)} \right) \]  

(28)

where \( U_R \) represents the uniform random number over \([0, 1]\), \( I_R \in [1, \ldots, N] \) denotes the index of the rooster which is the group-mate of ath hen. \( I_c \in [1, \ldots, N] \) indicates the index of the chicken which is randomly chosen from the swarm. \( I_R \neq I_c \).

It is obvious that \( F_a > F_{I_a} \) and \( F_a > F_{I_c} \) and hence \( Q_2 < 1 < Q_1 \). If it is assumed that \( Q_1 = 0 \), then the ath hen would search for the food followed by other chickens. The larger the gap between the placemant of two chickens, the smaller the \( Q_2 \) value, and the greater the difference between the fitness scores of two chickens. As a result, the hens would be less likely to steal the food that other chickens found. The fact that there are competitions within a group is the reason why the formula for \( Q_2 \) differs from \( Q_1 \). The ath hen would look for food within their own territory if \( Q_2 = 0 \). The rooster’s fitness value is particular to that group. The closer \( Q_1 \) is to 1, the narrower the difference between the position of the ath hen and its group-mate rooster, and the lesser the fitness value of ath hen. The more dominant hens will therefore be more likely to devour the food than the more submissive ones. In pursuit of food, the chicks would scurry about their mother chickens..

\[ P_{a,b}^{t+1} = P_{a,b}^t + FL \times (P_{M,b}^t - P_{a,b}^t) \]  

(29)

where \( P_{M,b}^t \) denotes the position of the mother of ath chick \((M \in [1, N])\). FL (FL \( \in (0, 2) \)) is a parameter denoting that the chick would follow the mother hen in search of food.
The Mean Square Error (MSE) between the estimated CSI and original channel CSI is computed at all pilot subchannels. The estimation of CSI is affected by the number of sub-channels and frequency selection. The CSI estimation performance is improved with the increase in the number of iterations.

### CSO Algorithm

- Initialization of population of ‘N’ chickens and passing the weights to the network
- Evaluate the fitness values of ‘N’ chickens, \( F = 0 \);
- Loading the training data to the network
- While \( \text{MSE} < \text{Stopping Criteria} \)
  - If \( (F \% \text{Gen} == 0) \)
    - Rank the fitness values of the chickens and establish a hierarchical order in the swarm;
    - Divide the swarm into various groups, and determine the relationship between the mother hens and chicks in a group;
  - End If
  - For \( i = 1:N \)
    - If \( i == \text{rooster} \)
      - Update its location;
    - End If
    - If \( i == \text{hen} \)
      - Update its location;
    - End If
    - If \( i == \text{chick} \)
      - Update its location;
    - End If
    - Evaluate the new solution;
    - If the new solution is better than the previous one, replace the previous solution with the new solution;
  - End For
  - Swarm finds the best weights and passes to the network;
  - Chicken keeps on calculating the best possible weight at each epoch until the convergence of network;
- End While

### Results

Simulation of the proposed algorithm is done using MATLAB 2014a. The simulation parameters are described in Table 2. The performance of the proposed Channel Selection (CS) with CSO algorithm is evaluated in terms of SE and EE by comparing with Fully Connected-Zero Forcing (FC-ZF) Precoding, Hybrid Precoding [53], Quantized Hybrid Precoding [54], B-MIMO Precoding [55] and CSO-Dynamic Phase Adjustment (DPA) [56]. Indumathi et al. [57] used the Hybrid Grey Wolf Optimization with Cuckoo Search algorithm to obtain the EE in massive MIMO systems. Figure 2 shows the comparison of the FC-ZF Precoding, Hybrid Precoding, Quantized Hybrid Precoding and B-MIMO Precoding. From the graph, it is found out that the SE increases with

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the increase in the SNR. By choosing the optimal channel for data transmission, the proposed scheme yields better performance than the conventional algorithms.

Figure 2 shows the analysis of Spectral efficiency for different precoding techniques. Figure 3 illustrates the comparative analysis of SE and EE for the proposed MIMO-CSO for various SNR values. It is observed that the SE increases with the increase in EE. The tradeoff between SE and EE is balanced by optimizing the power allocation and beamforming vectors using the CSO algorithm.

The proposed massive MIMO-CSO is compared with the existing near and sub-optimal schemes [58]. Figure 4 illustrates the EE Analysis of existing near and sub-optimal schemes and proposed massive MIMO-CSO for different number of users. The number

| Parameters                          | Value   |
|-------------------------------------|---------|
| Radius of cell                      | 1000 m  |
| Reference distance                  | 100 m   |
| Path-loss exponent                  | 3.8     |
| Shadow fading standard deviation    | 8 dB    |
| Target BER                          | $10^{-3}$ |
| Number of antennas in BS            | 128     |
| Number of users                     | 4       |
| Estimation error variance           | 0.1     |
| Noise power                         | $-104$ dBm |
| Power amplifier efficiency          | 0.3     |

Fig. 2 SE analysis of FC-ZF Precoding, Hybrid Precoding, Quantized Hybrid Precoding and B-MIMO Precoding
of users in our proposed scheme is 4. The near and sub-optimal schemes obtain similar EE performance with low complexity. The proposed massive MIMO-CSO achieves higher EE than the near and sub-optimal schemes.

Fig. 3 Comparative analysis of spectral and energy efficiencies for the proposed massive MIMO-CSO

Fig. 4 EE Analysis of existing near and sub-optimal schemes and proposed massive MIMO-CSO for different number of users
Table 3 compares the CSO algorithm complexity with other two algorithms. $I_1, I_2$ and $I_3$ are the number of iterations in Near-optimal algorithm and $I_4$ & $I_5$ are the number of iterations in sub-optimal algorithm [57]. $I_6$ is the CSO scheme number of iterations. From the Table 3, it is observed that the complexity is increased in CSO compared to other methods, but the performance graphs show that the EE is increased.

Figure 5 presents the SE Analysis of existing near and sub-optimal schemes and proposed massive MIMO-CSO for different number of BS antennas. The SE performance of the massive MIMO system is improved with the increase in the number of BS antennas as it brings greater spatial diversity gain. It is observed that the near-optimal scheme and sub-optimal schemes have similar SE with lower complexity. Especially for larger number of BS antennas, performance of the proposed massive MIMO-CSO is better than the near and sub-optimal schemes.

Figure 6 depicts the comparative analysis of the energy efficiency of the GA, PSO and CSO algorithms. Figure 7 presents the SE analysis of the GA, PSO and CSO algorithms. From the graphs, it is observed that the proposed CSO algorithm yields better SE and EE than the existing GA and PSO algorithms.
11 Conclusion

In the proposed work, the trade-off between SE and EE of the massive MIMO is balanced using the bio-inspired CSO algorithm. The main objective of the proposed scheme is to find the optimal solution for beam-forming vectors and power allocation and an optimal channel for the data transmission. The optimal solution has been found to attain maximum SE and EE through the RE metric model. CSO algorithm is applied to find the optimal
channel for transmission. The channel state information is predicted and a projection matrix with channel estimation framework is formed. The selection of the index sets in the iteration process provides the optimized channel. Data transmission is performed through the optimal channel. From the experimental results, it is concluded that the proposed CS scheme with the CSO algorithm yields better SE and EE than the existing algorithms.

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