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ORIGINAL RESEARCH ARTICLE

Enhanced chicken swarm optimization for channel estimation and low complexity hybrid beamforming over massive MIMO

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ABSTRACT

Massive Multiple-Input Multiple-Output (MIMO) systems with several antennas at the base station (BS) achieve overspatial degrees of freedom. It significantly increases energy and spectrum efficiencies, making it crucial technology for future wireless communications. Even with these alluring benefits, using a lot of antennas results in significant power and hardware costs. Additionally, the efficacy of hybrid beamforming is lacking in the current system, which has an impact on both system and energy efficiency. Enhanced Chicken Swarm Optimisation (ECSO) and energy-efficient Hybrid Analog-Digital (HAD) beamforming using Analog-To-Digital Converter (ADC) are used in this study to address the aforementioned issues. This research work includes main steps are system model, channel estimation and energy efficient ADC on MIMO systems. Initially, the system model is constructed using antennas, Radio Frequency (RF) chains and antenna users. Then, channel estimation accuracy is ensured by using ECSO algorithm. It generates best fitness values in terms of best channel and sum rate using local and global optimal values. K users concurrent in antennas are acquired to guarantee that channel coefficient estimates between antennas and, low complexity heuristic based on channel estimations can be carried out. Lastly, beamforming is accomplished by HAD both digitally and analogously where pilot sequence optimizations, HAD, and ADC quantization bits distributions reduce Mean Square Error (MSE) by working in paraleel for estimating channels. The ECSO-HAD outperformed other approaches in terms of spectrum efficiencies, greater sum rates, lower energy consumptions, and better Normalised Mean Square Error (NMSE) rates in simulation results.

Keywords: Massive Multiple-Input Multiple-Output (MIMO) systems; Hybrid Analog-Digital (HAD) beamforming; Analog-To-Digital Converter (ADC); Enhanced Chicken Swarm Optimization (ECSO); channel estimation

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1. Introduction

MIMO systems depend on multiple BS antennas to serve users concurrently while balancing spectral efficiency (SE) and energy efficiency (EE)[1–3], but many antennas eventually result in greater energy and money spent on radio frequency (RF) gears. Hence, in practical implementations, hardware-efficient HAD beamforming architecture was used instead of digital beamformer. This design specifically used low-dimensional digital beamformer in the base and and an analogue beamformer in RF domains to significantly reduce required RF chains. Consequently, the schema offered more design freedom and achieved desirable balances between complexity and performances. Since power consumptions of analog-to-digital converters (ADC) rise exponentially with quantization bit counts, ADC dominates power dissipations of receivers. As a result, for HAD receiver RF chains, low-resolution ADC (LADC) have been advocated.

The Orthogonal Frequency Division Multiplexing (OFDM) modulations with MIMO communications in broadband wireless channels, allow MIMO-OFDM systems to attain higher data rates. A blind channel estimating method was proposed[4] to generate bandwidth-efficient solutions for MIMO-OFDM channel estimates, based on a subspace approach and channel identifiability constraints. In singular OFDM outputs, we enhanced and merged previous subspace based blind channel estimate algorithms to create two unique MIMO-OFDM systems, separated by counts of transmitting and receiving antennas. The approach, specifically, yielded convergences and precise channel estimations that were insensitive to overestimations of real channel orders. The technique could function with no or little Cyclic Prefix (CP) if Virtual Carriers (VC) were available, which could also increase channel utilisations. Additionally, it was demonstrated that, under certain system conditions, the approach could produce accurate channel estimates with limited amounts of OFDM symbols and used on MIMO-OFDM systems without CP, even in the presence of VC. The technique thus increased the efficiency of transmission bandwidths. Numerical experiments demonstrated lower MSE of the approach in simulations.

Digital hardware can process physical signals using analog-to-digital conversions which encompass two steps namely quantizations, or encoding continuous amplitude quantities with limited number of bits, and sampling are processes of converting continuous time signals into discrete data. When operating at high rates and fine resolutions, conversions can be costly as they often perform using generic uniform mappings of signals collected. ADC learnt to transform analogue signals into sampled digital representation in successful systems[5]. They function in a data-driven way. It made use of a sampling and quantization approach that allows systems to learn non-uniform maps from trained data while representing these operations accurately. We address the symbol detection challenge in MIMO digital receivers, where a collection of discrete information symbols is recovered by concurrently acquiring multiple analogue signals. The numerical findings show that, in comparison to using traditional uniform ADC, the technique delivers more accurate digital representation while providing performance that is equivalent to operating without quantization limitations.

HAD beamforming designs have made it easier to deploy huge MIMO systems in real-world applications by using fewer radio frequency chains. They employed two phase HAD beamforming topologies on multi-user MIMO systems that maximized systems' EE or SE where most studies focused on maximizing SE[6]. The combined optimisation of the digital and analogue domains, as well as the constant modulus limitations imposed by the analogue domain, make this issue NP-hard and nonconvex. It employed a decoupled two-stage design to solve this issue. Analogue beamforming components are updated in first phases while in second phases digital beamforming components improve system's EE or SE. This work's HAD beamforming approaches used variable phase shifter based Fully-Connected (FC) or Partially-Connected (PC) architectures. The performances of the dual HAD designs were examined with fully-digital (FD) architectures for circuitry power consumptions and obtained SE/EE based on available data of circuitry power components. In comparison to the PC designs, which consistently used lower circuitry power consumptions, the study observed that above certain user counts, FC architectures had greater circuitry power consumptions than their FD equivalents. More importantly, their results demonstrated FD design's capability to achieve higher SE and EE than other HAD systems.

This study concentrated on antenna selection, which is a viable strategy for reducing complexity and expense in huge MIMO configurations. In some huge MIMO setups, the antenna selection can also improve energy efficiency when compared to the case of complete antenna selection, as shown by the numerical results for energy efficiency[7]. We investigate a large MIMO system where transmitters use constant sized subsets of strong accessible antenna gains and as transmitting antenna counts are considerable, mutual input-output information in this design is approximated by normal random variables[8].

Effects of transmitting antenna selections on giant MIMO systems' secret performances are examined from Asaad et al.[9]. The study considered wiretap scenarios where fixed transmitting antenna counts were selected, and used for secret communications to multi-antenna recipients with interceptions from multi-antenna eavesdropper. They obtained precise approximations of secrecy rates in configurations which demonstrated that under certain wiretap circumstances increasing counts of active antennas improved system's secrecy but also reduced after a certain limit. This discovery showed that in some huge MIMO scenarios, choosing the right antennas not only improved secrecy performances but also lowered RF-complexities.

In this research, ECSO is proposed to address slow convergence speeds and avoiding slipping into local optimum while handling high dimensionality information. The enhanced CSO, also known as ICSO-RHC, is composed of four positional update strategies for populations, hens', chicks' and cocks. The impact of control settings and retained elite counts on the algorithm's speed of convergence is examined in light of algorithm enhancements[10]. The test function's calculations demonstrate that evenly distributed random number between [0, 1] control elite population to 1 with quick convergences.

ICSO incorporates improved strategies namely local searches, weighing factors, and global searches in updates of traditional CSO algorithms to enhance beam pattern optimisations of array antennas[11]. Moreover, suggested variations enhance population variety and algorithm performances.

Although many studies and approaches have been presented, there is still a considerable lack of accuracy in channel estimation; ensuring accuracy of channel estimates in MIMO systems is the main focus of this research work. The current methods in MIMO have issues with spectral efficiency and EE. The ECSO-HAD technique is employed in this study to enhance MIMO system performances in order to address the aforementioned problems. The system model, channel estimation using the ECSO method, energy-efficient ADC, and HAD beamforming over multiuser MIMO are the primary contributions of this research. The suggested approach uses efficient techniques for the multiuser MIMO to produce outcomes with a greater total rate and reduced energy usage.

The remainder of the paper is structured as follows: Section 2 provides a brief overview of the literature on channel estimation, energy-efficient ADC, and HAD beamforming on MIMO. Section 3 provides specifics on the suggested ECSO-HAD algorithm technique. In Section 4, the performance analysis and simulation findings are presented. Section 5 provides a summary of the conclusions.

2. Related work

He et al.[12], stated that in beamspace millimeter-wave huge MIMO systems, When receivers are limited in their RF chain counts, channel estimations become extremely challenging. The Learned Denoising-based Approximate Message Passing (LDAMP) network was used to remedy this. Neural networks require a lot of training data to estimate channels and understand their architecture. Moreover, they offer mathematical frameworks for evaluating channel estimators' asymptotic performances. The results of analysis and simulations reveal that, even with restricted RF chains inserted in receivers, LDAMP neural networks outperform other compressed sensing based approaches.

Lin et al.[13] investigated channel estimation in mmWave MIMO systems with downlink IRS assistance. They shandled channel estimations as fixed rank restricted non-convex optimizations using sparsity of mmWave channels. Utilising alternating minimization and Manifold Optimization (MO), an effective technique is applied to address the non-convexity and produce a locally optimum solution. The findings of the simulation indicate that the MO-based estimate (MO-EST) method performs much better than two benchmark schemes and shows that, in real-world applications, the algorithm is resilient to incomplete information of channels' sparsity levels.

The uplink of multiuser large MIMO systems was investigated utilizing mixed ADC architecture Ding et al.[14] where BS was furnished with ADC of variable resolution levels. Higher resolutions and ADC required more energy in order to increase performances by reducing quantization errors. This work studied maximum-ratio combined receiver's receive EE and ADC resolution profile design. Initially, using generic mixed ADC structures, closed-form approximations for SE and receiving EE were developed. Subsequently, optimization issues for ADC resolution profile were designed to maximize receiving EE while meeting SE requirements. Their method had a complexity linear to BS antenna counts and was based on decremental searches and dynamic programming. Their numerical findings confirmed that their design allowed mixed-ADC receivers to achieve equal SE performances while consuming significantly smaller amounts of energy.

Liu et al.[15] examined impacts of signal detection strategies on uplink MIMO systems' EE using low-resolution ADC. They included perfect/imperfect Channel State Information (CSI) in power allocations and analytical approximations of Zero-Forcing (ZF) and ZF Successive Interference Cancellation (ZF-SIC) receivers with the assumptions of equal transmission rates for all users. Their EE comparisons on ranges of receivers revealed that, although ZF-SIC receivers required smaller counts of BS antennas than ZF receivers, large counts of antennas were required to compensate quantization errors resulting in significant RF circuit power consumptions for uplink massive MIMO systems with low-resolution ADC. As a result of decreasing dimensionalities and reusing the receiver weights of coherent blocks, ZF-SIC signal processing now consumes more power. ZF-SIC receivers could thus increase overall EE for huge MIMO systems with workable ADC. Additionally, the study approximated multi-cell situations, taking into account inter-cell interferences and pilot contaminations.

FD mmWave MIMO systems with hardware-efficient dynamic subarrays were built by Wang et al.[16]. A hybrid beamforming strategy was used in the study to efficiently negate Self-Interference (SI) in the systems. Initially, up/downlink channels were dissected and water-filling powers were assigned to generate optimum digital beamformers and combiners under no SI assumptions. They then extracted dynamic analogue solutions from acquired digital solutions assisted by dynamic hybrid beamforming designs using Kuhn-Munkres algorithm. Finally, they projected resulting digital beamformers into null spaces of equivalent SI channels in order to cancel SI at BS using null space projections. The computational complexity of using mmWave half-duplex communications and fixed subarrays were examined where the suggested approach using constant subarrays and half-duplex mmWave communications with six RF chains and signal-to-noise ratio as ten decibels performed better in terms of EE when compared to FD mmWave MIMO systems.

Ardah et al.[17] proposed a two-stage HAD beamforming solution that may be utilized to maximize the total EE or SE of multi-user MIMO systems. Combined optimizations of digital and analogue processes with modulus limitations imposed by analogue domains, makes the issue of EE, a NP-hard and nonconvex issue. In order to solve this issue, a decoupled two-stage design was employed, in which the analogue beamforming components were updated in the first stage while designing digital beamforming components in the second stage in order to optimize system's EE or SE. Two popular HAD beamforming methods that made use of FC or PC designs with variable phase-shifters used current information on the components' circuitry power consumptions, in terms of overall circuit power consumptions, the two HAD designs were contrasted with Fully-Digital (FD) architectures for values of SE/EE. The study discovered that, in contrast to PC design, which consistently had lower circuitry power consumptions, there existed a threshold at which FC architecture had higher circuitry power consumptions than its FD equivalents. More significantly, the results showed that, in contrast to popular belief, FD designs produced higher EE and SE than HAD architectures, depending on circuitry parameters.

Tan et al.[18] proposed huge MIMO system Mixed ADC (M-ADC) architectures for examining SE and EE. The M-ADC design allowed, in theory, for one portion of antennas at BS to be linked to speedy, costly full-resolution ADC while remaining antennas were attached to inexpensive, low-resolution ADC. The universal maximum-ratio combining detectors were applied yielding tractable approximations for feasible SE. Based on deduced outcomes; impacts of quantity of BS antennas and percentage of full-resolution ADC on attainable SE were examined. The obtained results indicate that BS antenna counts and percentages of full-resolution ADC both enhance possible SE. For the given M-ADC design, the study assessed EE using realistic power consumption models. Furthermore, they optimized EE by varying low-resolution ADC counts and resolution bits of related ADC devices, all within specific attainable SE restrictions. Their use of mixed-ADC architectures showed great potential for usage in future mobile communication systems as demonstrated by their numerical results showed increasing average transmitted powers resulted in the existence of ideal resolution bit counts and antennas that maximized EE.

3. Proposed methodology

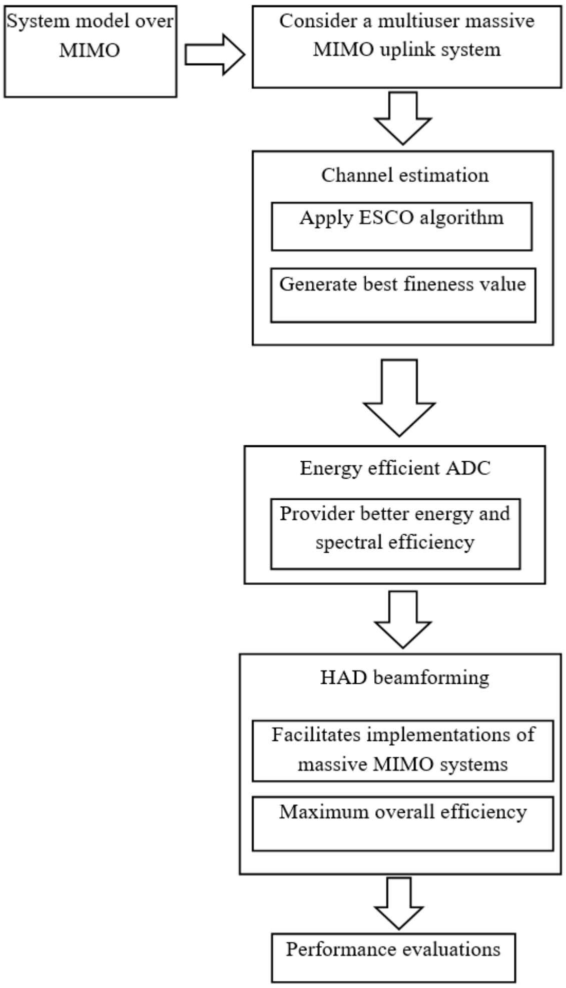

Figure 1. Overall block diagram of the proposed system.

In this work, ECSO-ADC approach is suggested for enhancing performances of MIMO systems. The system models and channel estimations using ECSO method, energy-efficient ADC, and HAD beamforming over multiuser MIMO are the primary contributions of this research work. The proposed work's general block diagram is displayed in **Figure 1**.

3.1. System model

Multi-user massive MIMO uplink systems with ADC at BS and static FC hybrid AD are combined in this work. BS serves K single-antenna users concurrently due to M > 1 antennas and N ≪ M RF chains. The baseband outputs of RF chains are routed to customized ADC, which quantizes real and imaginary components of analogue signals using variable bit resolutions and additionally BS synchronize their time with users. MIMO systems use many antennas to transmit streams and pathways between transmitting antennas at transmitters and receivers make up matrix channels that transmit streams. Analysis of antennas' impacts on MIMO performances is pertinent to developing apt antenna array structures.

Channel model:

Narrowband correlated channel model without losing generality is examined. Assuming $h_k \in C^{M\times 1}$ represents users' uplink channels $k \in K = \{1, \dots, K\}$ to BS, channel vectors h_k can then be written as

$$h_k = R_k^{1/2} g_k \tag{1}$$

where $g_k \in C^{M\times 1}$ represents similarly independent element distributions (i.i.d.) as CN(0,1) $R_k = E[h_k h_k^H]$ signifies channel matrices of covariances of users k, and. R_k signifies channels' spatial correlations caused by macroscopic propagations including path-losses and shadows. Path-losses and shadows can be computed for quasi-stationary users using known distances between BS and users.

MIMO channel capacity is represented by

$$Q = E[xx^H]$$

It is the input covariance matrix, where N_0 is the noise power in each receive-side antenna and E_s is the overall transmit power.

$$\text{Quantization errors of ADC} = 20 * \log(\tfrac{1}{2}^{\wedge} n)$$

$$\text{SNR(dB)} = 20\log\frac{rmssignal}{rmsnoise}$$

3.2. Subsection Channel estimation in multi user MIMO systems via ECSO algorithm

In this study, the ECSO method is used to obtain accurate channel estimate. In its original configuration, massive MIMO operates by means of each K user at the BS receiving the sent pilot sequence. Channel coefficients between BS antennas and users are then calculated using suitable estimations. **Figure 2** depicts the system model for the massive MIMO CSI estimation problem.

Estimations of Minimum Mean Square Error (MMSE) maximize results by using 2nd order channel characteristics which can be mathematically depicted as:

$$\widehat{H} = YP^H[\sigma_z^2 I_M + P^H P]^1 \tag{2}$$

The inverses of covariance matrices with cubic computational complexities in matrix dimensions generated by products of antenna counts at BS and training sequence durations are computed. These clearly show higher computation costs and channel estimations that cannot be completed within coherence time constraints.

Low Complexity Heuristic Based Channel Estimation:

Critical demands for low complex channel estimators in Massive MIMO systems motivate formulations of channel estimation issues as optimisations. The channel matrices are computed using Euclidean distance g between estimated and original channel coefficients, as shown below.

$$F(Y, \widetilde{H}) = \min\{||Y - \widetilde{H}P||^2\} \tag{3}$$

where Y represents received training signals at BS transmitted by K users and $\widetilde{H}$ stands for estimates of channel matrices H.

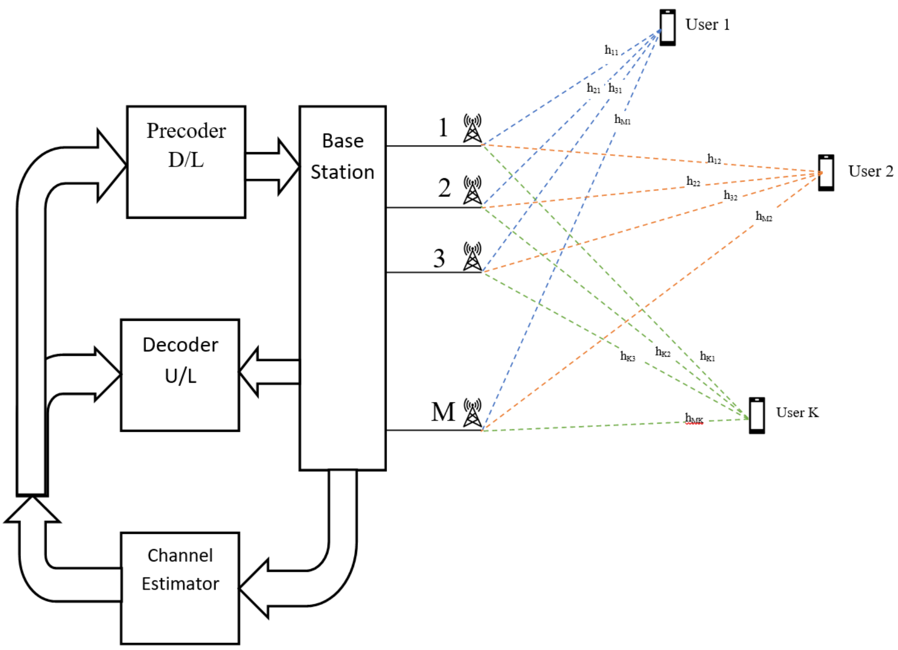

Figure 2. System model for CSI estimation problem in massive MIMO.

The suggested method uses optimisation to reduce the function that is specified by Equation (3). Primary concept is to partition the M × K dimensional search space issue into M K × 1 dimensional search spaces. As a result of parallel processes at BS, the issue of channel coefficient estimations between mth BS antenna and K users were obtained concurrently for antennas.

This study proposes ECSO as an effective channel estimation approach. Problems may be ideally addressed by successfully extracting the intelligence of the chickens using a revolutionary bio-inspired algorithm dubbed CSO; this is modelled like swarms of hierarchical chickens (roosters, hens, and chicks). CSO selects features to minimize features while scouring feature spaces for optimal feature combinations for optimized classification performances. The programme mimics both the actions of individual chickens and the hierarchical structure of a swarm of chickens. There are several hens and chicks in hierarchical swarms of chickens, led by roosters within groups. Different chicken types adhere to different rules of mobility. Hens' social life are greatly impacted by hierarchical patterns, wherein stronger chicks in flocks exercise power over weaker ones. While dominating hens stay nearer to head roosters and are positioned at the perimeter of the group. **Figure 3** is CSO algorithm diagram.

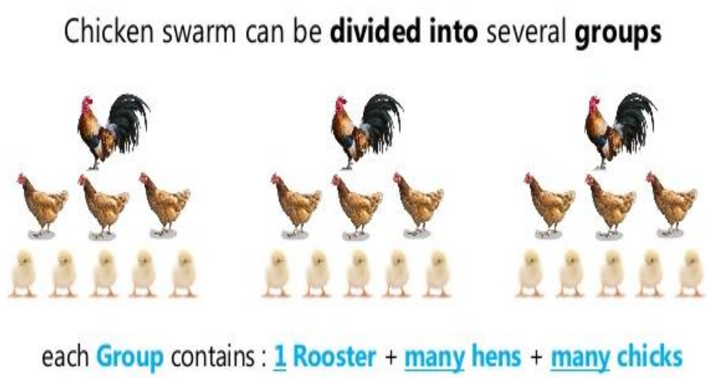

Figure 3. Nature of CSO algorithm.

Chickens Movements:

Rooster Mobility: More fit roosters forage food in more locations.

Hen movement: In order to get food, hens follow the roosters in their flock. In a competition for food, the more assertive chickens have an edge over timid chickens.

Chick mobility: In order to get nourishment, the chicks move about their mother.

The following guidelines, which encapsulate the behaviours of the chickens, are the foundation of the mathematical model of CSO put forward in Ahmed et al.[19]:

1) There are many groups inside chicken swarm where roosters dominate groups, followed by hens and chicks.
2) Swarm hierarchies are determined by fitness values of chickens; roosters with highest fitness values are leaders, while chicks with lowest fitness values are individuals.
3) In group mother child bonds are dynamic dominances and do not get altered by swarm hierarchy. Time steps update statuses.
4) The swarm is made up of n virtual chickens, which are separated into the following groups: R_n, H_nC_n, and M_n, which represents counts of roosters, hens, chicks, and mother hens, in order. Positions of each person in a D-dimensional space are represented by

$$x_{i,j}(i \in [1,\ldots,N], j \in [1,\ldots,D]) \tag{4}$$

when it comes to food availability, Roosters with higher fitness levels are given precedence over those with lower fitness values. For the purpose of simplicity, this example may be duplicated assuming roosters with higher fitness values explore wider ranges of food. Since, normal CSO has a high error rate, Gaussian distributions are used to drastically minimize error rates. ECSO can be established as:

$$x_{i,j}^{t+1} = x_{i,j}^{t} * (1 + Randn(0, \sigma^2)) \tag{5}$$

$$\sigma^2 = \begin{cases} 1, \ if\ f_i \leq f_k \quad k\epsilon[1, N], k \neq i \\ \exp\left(\dfrac{(f_k - f_i)}{|f_i| + \varepsilon}\right), \quad \text{otherwise} \end{cases} \tag{6}$$

where Randn (0, σ^2) signifies Gaussian distributions having zero means and usage of standard deviations σ^2 avoid errors from zero divisions, ε stands for smallest constants k implies random, rooster indices from groups, f stands for fitness values of corresponding x.

The hens may get food by following the roosters in their flock. In addition, it would stifle the other birds' attempts to grab the tasty food that they had located. In a competition for food, the more assertive chickens would have an edge over the more timid ones. This is how these phenomena may be expressed numerically.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S_1 * rand * \left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S_2 * rand * (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{7}$$

$$S_1 = \exp\left((f_i - f_{r1})/(abs(f_i) + \varepsilon)\right) \tag{8}$$

$$S_2 = \exp\left((f_{r2} - f_i)\right) \tag{9}$$

where rand implies random values in the interval [0, 1]. $r1\epsilon[1,..N]$ represents rooster indices of ith hens' group mate', $r2\epsilon[1,..N]$ implies indices of randomly selected chickens (roosters/hens) from swarms $r1 \neq r2$.

Obviously, $f_i > f_{r1}, f_i > f_{r2}$, thus S2 <1< S1. Assuming S1 = 0, the *i*-th hen would go in search of food first, followed by the other hens. The S2 value and the distance between the two hens' places increase with the size of the gap in fitness scores between them. Hens generally do not steal food found by other chickens and hence S1 and S2 differ. Fitness values of chickens in relation to roosters' fitness values are duplicated for their competence. When S2 = 0, *i*-th hens search food inside their own domains where roosters have unique fitness values[19,20]. Therefore, the closer S1 gets to 1 and the closer its location is to the rooster in its group, the lower the fitness value of the *i*-th hen. Consequently, there's a higher likelihood that the dominant hens than the submissive ones will eat the meal.

Chicks roam about their mother for nourishment which can be expressed as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \tag{10}$$

where $x_{m,j}^{t}$ represents positions of ith chicks' mother' ($m\epsilon[1,N]$). $FL(FL\epsilon(0,2))$ represents parameters for chicks following their mothers for food. FL of chicks would be randomly selected in the range of 0 and 2 based on differences. By using the best fitness values, this calculates the global optimal solutions. When users are classified into sub-bands, the ECSO method may be utilized to determine the best transmit power distribution due to its efficient searching capabilities.

Algorithm 1 ECSO

```
Inputs: Populations of n chickens (multiple users and channels)
Outputs: Best solutions x_best (best channel estimations)
Initialize R_n, H_n C_n, and M_n
Evaluate fitness of N chickens', t=0; (max. transmission powers)
While t < Maximum iteration do
If t%G==0 then
Create hierarchies in swarms by ranking fitness of chickens.
Sort swarms into smaller groups, then observe how groups' chicks and mother hens interactions.
End
For i=1 to M channels do
If i==rooster then
Use (5) to update the solution
End if
If i==hen then
Use (7) to update the solution
End if
If i==chick
Use (10) to update the solution
End if
Evaluate the new solution
Update it if the newly created solution proves to be superior to the prior one.
Out of all the channels, select highest values of fitness
End
End
Give the best possible channel estimate accuracy and sum rate as a result
Return x_best (optimal channel estimation)
```

This technique uses the random location of the channel in huge MIMO systems to allocate and determine the chicks. In order to improve the appropriate channel, as outlined in Algorithm 1, chickens with highest fitness are updated. Determining which hens (channels) have global best search fitness value by computing best values for all chickens (users) and utilising Equation (10). The suggested solution uses ECSO for identifying channel combinations that maximize transmission powers while using minimal counts of selected antennas. Maximizing transmission power and channel estimation performance over multiple user MIMO systems is the ECSO's fitness function. Through the use of optimum fitness values, it offers a greater sum rate and improved channel estimate accuracy.

3.3. Energy efficient ADC and HAD Beamforming over multi user MIMO

In this work, energy-efficient ADC is employed. Using HAD combiners and ADC quantization bits, multi-user massive MIMO can provide highly precise uplink channel estimates. During uplink training, users concurrently broadcast pilot sequences used by BS to determine uplink channels. Regarding *k*-th users, BS's received pilot signals may be expressed as

$$Y = h_k s_k^T + \sum_{i \neq k}^{K} h_i\, s_i^T + Z \tag{11}$$

where first terms represent needed k user contributions while second terms represent multi-user interferences, and $Z \in C^{M \times T}$ signifies additive complex Gaussian noise matrices with i.i.d. entries following distributions CN (0, σ2). Received signals Y are processed at BS using analogue combining matrices U ∈ C N×M for preventing interferences from other users. Phase shifters are commonly used in the HAD design to construct the analogue combiner[21], which places constant-modulus restrictions on the matrix U's components. The analogue combiner's output is provided by

$$\bar{Y} = U\left(h_k s_k^T + \sum_{i \neq k}^{K} h_i\, s_i^T + Z\right) \tag{12}$$

It uses an ADC to quantize Y because it allows for adjustable quantization bit assignments for baseband channels based on radio propagation parameters. This improved architecture can enhance system performance a while lowering hardware prices and power consumption along with quantization errors. The integer bn represents quantization bit counts accessible to ADC n. Additive Quantization Noise Model (AQNM), the quantized signal may be reformulated. Following that, the quantized output is tailored to

$$Y_q = F(\bar{Y}) = Q_\alpha \bar{Y} + Z_q \tag{13}$$

where $F(\cdot)$ is the element-wise quantization function, $Q_\alpha = diag(\alpha 1, \ldots, \alpha N)^{R^{N\times N}}$ implies diagonal gain matrices. It contributes to the reduction of power consumption in big bandwidth massive MIMO receivers. It ensures ideal EE while demonstrating usage of variable-resolution (VR) ADC in Ma-MIMO receivers for enhancing EE while enhancing throughput and Mean Squared Error (MSE) performances. Under power constraints, the best energy-efficient ADC for Ma-MIMO receivers with ADC is described in this study[22]. It is employed to maximize EE while limiting power. It demonstrates the considerable decrease in computing complexity.

Subsequently, beamforming is handled by HAD in both the digital and analogue realms. A potential method that makes use of both high matrix analogue beamforming and small matrix digital precoding is HAD beamforming. Analogue phase shifters, which merely alter the signal's phase, are used to modify the signal at the element level. Precoding or combining is therefore actually done in two steps.

The fundamental obstacle that many researchers have when working with big antenna arrays is that the completely Digital BeamForming (DBF) that is thought to be possible in sub-6GHz bands will not be possible because of problems with power and complexity. This is because the specialised RF chain only has one antenna. However, Analogue BeamForming (ABF) offers a more energy-efficient option. It's one data stream constraint, however, typically results in significant performance restrictions when used with several users. In order to overcome these obstacles, an HBF solution is a viable strategy that makes use of high matrix analogue beamforming and small matrix digital precoding.

The antenna counts and RF chains at BS are amongst communication networks. Each RF chain is outfitted with all the necessary antennas to service K mobile stations concurrently and send Ns data streams. Every user has one RF chain and the necessary antenna counts to receive data streams. It was believed that each user transmitted a single stream transmission in order to simplify the challenge. The overall architecture of analogue and digital beamforming is seen in **Figure 4**.

Figure 4 illustrates how the suggested communication system combines analogue and digital systems. The source and relay stations, according to this figure, provide service to K decentralised destinations, with Ms, Mr, and Md (Ns, Nr, and Nd RF chains) representing the antenna counts (RF chains) at the source, relay, and each destination, respectively.

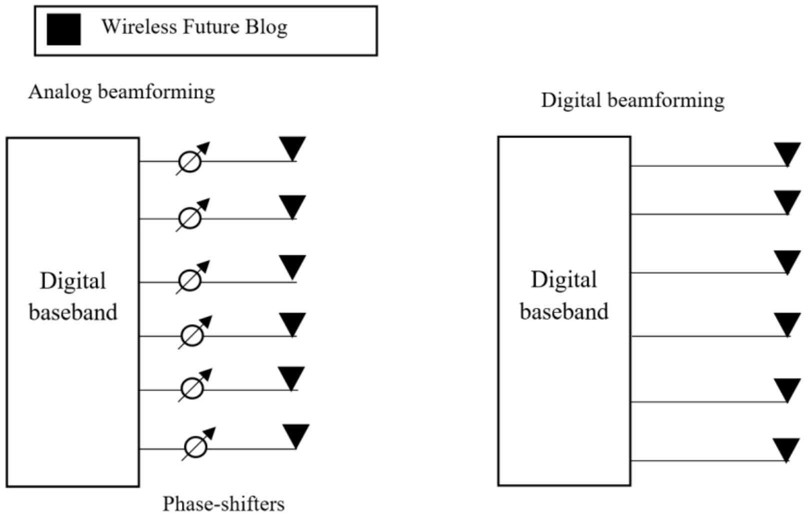

Figure 4. General structure of analog and digital beamforming.

It provided an overview of the traditional digital beamforming relay network architectures for easier understanding of the parts that followed. The hybrid beamforming design uses the digital beamformer's solution, as was covered in the introductory section. Though many digital beamforming algorithms are now in use, this work uses BD beamforming methods employed in Xue et al.[23] for reduced complexity and can be summed up as:

Assuming same antenna counts at different destinations exists for the typical digital beamforming relay systems, signals received at kth destinations can be represented as

$$Y_k^D = \widetilde{W_{dk}^H} H_k^H \widetilde{W}_r G \widetilde{W}_t s + \widetilde{W_{dk}^H} H_k^H \widetilde{W}_r n_r + \widetilde{W_{dk}^H} n_{dk} \tag{14}$$

where $\widetilde{W}_r$, $\widetilde{W}_t$ and $\widetilde{W_{dk}}$ are digital beamforming at relays, sources, and destinations. They currently use BD beamforming of Xue et al.[23] where beamforms are generated in two phases.

Since it is difficult to solve issue Equation (14) directly, sources, beamforming matrices at destinations and relays are optimised. We optimise Wdk and Fdk separately for every destination in the first step. In the second stage, the relay beamforming matrices Fr1, Fr2, and Wr are optimised for the first stage's provided Wd and Fd. In the third stage, the source beamforming matrices Ft and Wt are optimised while Fr1, Fr2, Wr, Wd, and Fd are kept unchanged. More specifically, the beamforming matrices at the source and destinations are obtained using the MP technique. At the relay station, we generate the hybrid beamforming matrices using a two-step process. In order to generate several beams and so reach many users with different intensities, it combines both digital and analogue processes. **Figure 5** displays hybrid beamforming architecture. The hybrid beamforming design at the relay separates analogue and digital beamforming into two phases. We use transmit-receive coordinated analogue beamforming even for different array topologies to examine enormous array gain not only at the base station but also, and especially at the relay.

$$\min_{F,W} ||D_1, FW - D_2||_F^2 \tag{15}$$

$$\text{s.t trace } (FWW^H F^H) = P \tag{16}$$

$$|F(i,j)|^2 = 1 \tag{17}$$

where F implies analogue beamforming matrices and W stands for digital beamforming matrices with similar mathematical structures[24] amenable to efficient solutions.

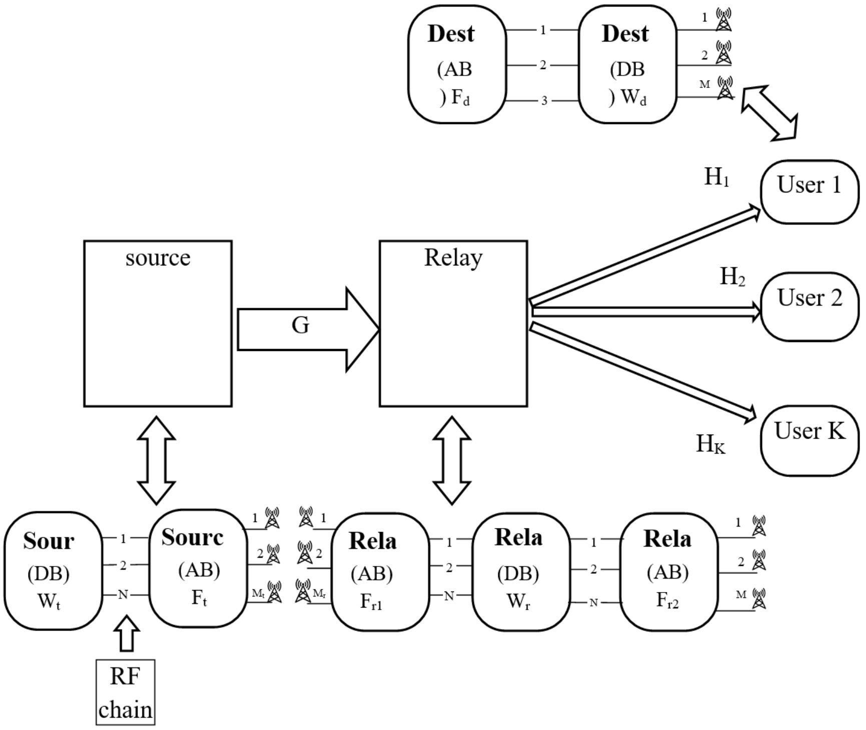

Figure 5. Hybrid beamforming architecture.

3.4. The simulation's outcome

Subheadings may be used to organize this section. It should give a clear and simple explanation of the experimental findings, their meaning, and any inferred experimental implications. The simulation results for the suggested hybrid beamforming and channel estimation architecture are shown in this section. This section includes simulations to verify the performance of suggested and current methods. We present simulation findings on the total uplink attainable SE in this section. Cell radii in simulations are set to rc = 1000 m, guard zone radii as rh = 100 m, decay exponents as γ = 2.1, and shadow-fading standard deviations as σ_{shad} = 4.9 dB. BS located in the center of cells are equipped with M = 64 antennas and N = 12 RF chains. A total of K = 12 users are uniformly distributed within the cell area. Size of frequency operation band is fourth-generation (4G) user equipment with the frequency band of 2.6 GHz, central frequency of operation is frequency bands/modes, 2.4 GHz to 3.5 GHz, waveform of signal R = 1 M X X H is the waveform covariance matrix. Various techniques, including the current LDAMP[7], M-ADC[13], and the ECSO-HAD algorithms that have been developed, are taken into account for assessing performance measures such as MSE, sum rate, spectrum efficiency, and energy consumption.

With a vast amount of training data, LDAMP can estimate the channel and learn about its structure. The M-ADC design allows for the connection of a portion of the antennas at the base station to high-speed, high-cost full-resolution ADCs and the remaining portion to low-cost, low-resolution ADCs.

Sum Rate:

The total of all the communication rates occurring inside a network is known as the sum rate. The following is rather obvious: Your nodes can send more data the longer they can interact.

Energy usage:

EE is the most important measure in the huge MIMO technique. Counts of BS antennas in proportion to counts of active users need to be optimised to identify EE trade-offs for MIMO uplink transmissions. Efficiencies of antennas are defined as power supplied to antennas divided by power emitted by antennas. Highly efficient antennas radiate most of the input power.

SE:

The total spectral efficiency of all transmissions within a cell in a cellular network is often what we mean when we talk about spectral efficiency. Bit/s/Hz is used to measure it. It may be multiplied by the bandwidth to obtain the cell throughput in bits per second. Through the use of coherent transceiver processing and the deployment of antenna arrays with hundreds of thousands of active elements at BS, massive MIMO is a viable method to boost the SE of cellular networks. Spectral efficiency.

$$\eta_S = B/\Delta v_{ch} \tag{18}$$

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

Normalized Mean Squared Error (NMSE):

Normalized MSE (NMSE) is used for evaluating channel estimation performances of schemes and defined

$$NMSE_k = \frac{1}{N}\sum_{n=1}^{N}\frac{||\hat{h}_k^n - h_k^n||^2}{||h_k^n||^2} \tag{19}$$

where $\hat{h}_k^n$ is the MMSE estimate of the k-th user's channel

Sum rate:

From **Figure 6**, it can observed that the comparison of existing LDAMP, M-ADC and proposed ECSO-HAD algorithms in terms of sum rate. In x axis we plot users counts and in y axis sum rate values are plotted. From the **Figure 6**, the sum rate values are lower by using LDAMP and M-ADC methods whereas the sum rate value is increased significantly by using the ECSO-HAD algorithm. It makes it possible to determine the ideal ratio between the power transferred and consumed at the RF links. As a consequence, the outcome demonstrates that the suggested ECSO-HAD algorithm offers multiuser MIMO systems efficient and optimum performance.

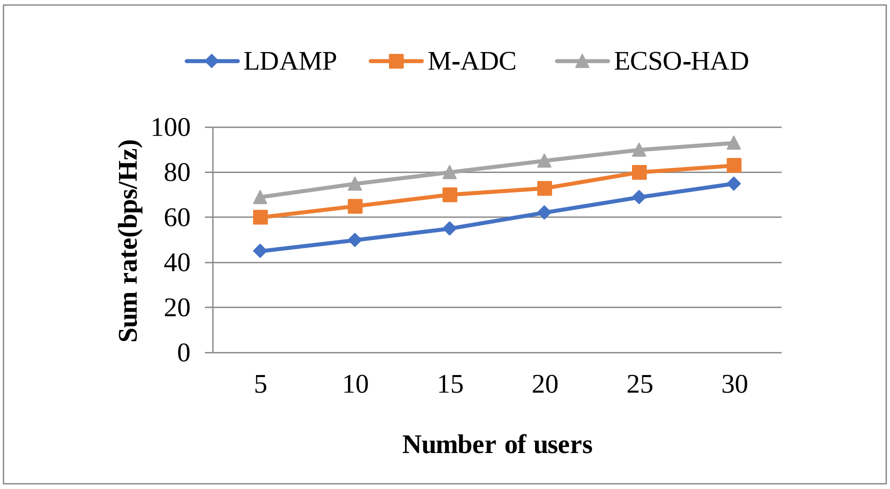

Figure 6. Sum rate.

Energy consumption:

The comparison in energy usage between the suggested ECSO-HAD algorithm and the current LDAMP and M-ADC methods is evident from **Figure 7**. Both the x- and y-axes' energy consumption metrics are measured. The x-axis measures distance. When compared to LDAMP and M-ADC algorithms for huge MIMO systems, the ECSO-HAD algorithm greatly reduces energy usage. In the uplink of multiuser huge MIMO systems, it is utilised to optimise the amount of ADC quantization bits and the hybrid receiver combiner. Based on the outcome, it was determined that the suggested ECSO-HAD algorithm outperforms the current techniques in multiuser MIMO systems.

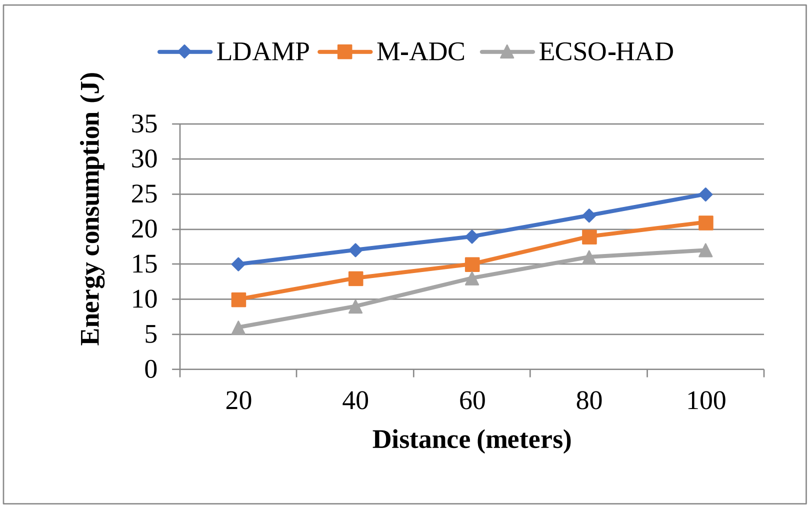

Figure 7. Energy consumption.

Spectral efficiency:

Figure 8 illustrates the comparison between the existing LDAMP, M-ADC and proposed ECSO-HAD algorithms for the spectral efficiency metric. Antenna counts form the x-axis, while spectral efficiencies are depicted on the y-axis. It demonstrates that while the ECSO-HADC approach offers greater spectrum efficiency, the LDAMP and M-ADC methods give lesser spectral efficiency. With fewer RF chains, it can get spectral efficiency that is nearly identical to the best completely digital system. Based on the outcome, it was determined that the suggested ECSO-HAD algorithm outperforms the current techniques in multiuser MIMO systems.

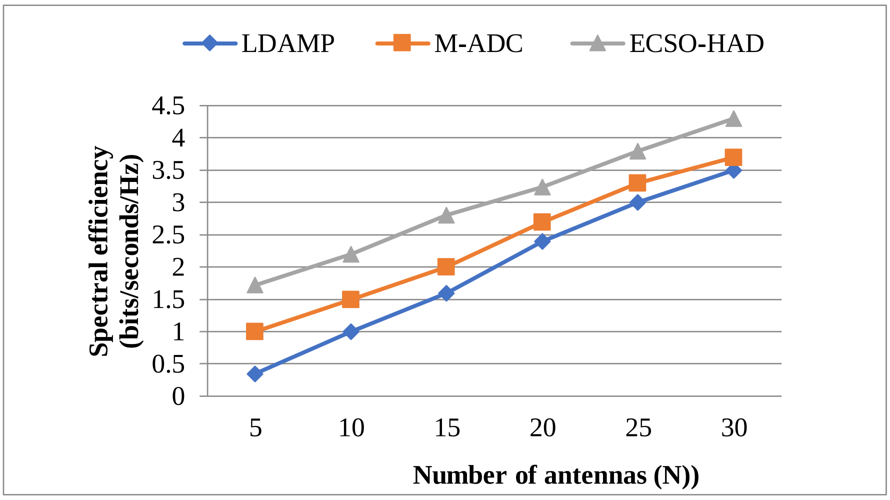

Figure 8. Spectral efficiency.

NMSE:

It is evident from **Figure 9** that the comparison metric is assessed using the current MSE techniques. X-axis represents techniques with their MSE values on y-axis. While LDAMP and M-ADC approaches yield greater MSE rates, the suggested ECSO-HAD method yields lower NMSE. Consequently, the outcome indicates that the suggested ECSO-HAD technique improves MIMO system performance by greatly lowering error rates.

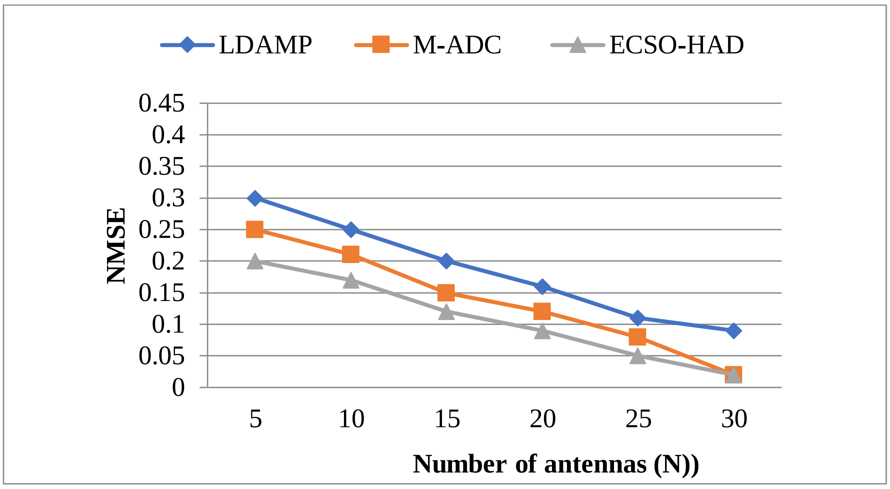

Figure 9. NMSE.

4. Conclusion

The ECSO-HAD technique is put forth in this study to optimize channel estimation over multiple user MIMO systems. The system model, channel estimation using the ECSO method, energy-efficient ADC, and HAD beamforming over multiuser MIMO are the primary contributions of this research. First, the system model is built, and then the ECSO method is used to estimate energy-efficient channels. Low complexity heuristic-based channel estimation is used to ensure that channel coefficient estimates between each antenna and each of the K users are gathered concurrently at each antenna. Lastly, beamforming is accomplished by HAD in both the digital and analogue domains. The suggested ECSO-HAD algorithm performs better in terms of a greater sum rate, a lower NMSE, a lower energy consumption, and a higher spectrum efficiency, according to the simulation results. Analysis of the suggested framework's performance in a MIMO-IoT network may be the goal of future research. Moreover, hybrid swarm optimization may be created to address computational complexity problems in a significant way.

Author contributions

Conceptualization, MK, SN and PR; methodology, MR; software, MK; validation, SN, PR and MR; formal analysis, MK, SN, PR and MR; investigation, MR; resources, MK; data curation, SN; writing—original draft preparation, PR; writing—review and editing, MR; visualization, MK, SN, PR and MR; supervision, SN; project administration, PR; funding acquisition, MR. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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