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Genetically Optimized Massive MIMO System for Enhanced QoS in 5G Networks

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Abstract
The paper shows simulation results and the analysis of a massive MIMO system optimized by Genetic Algorithm (GA) in downlink precoding. The performance of the system is determined in respect to Bit Error Rate (BER), Symbol Error Rate (SER), Spectral Efficiency (SE), Energy Efficiency (EE), and Channel Capacity at different Signal to Noise Ratio (SNR) conditions. A complete Genetic Algorithm is also proposed to minimize the precoding matrix that finally leads to maximization of sum rate of the system. It has been seen through the simulation that the quality of service (QoS) metrics is significantly improved by evolutionary optimization, which makes GA a feasible option in precoding of real-time Massive MIMO in 5G networks.

Keywords: 5G, Bit Error Rate, Channel Capacity, Energy Efficiency, Genetic Algorithm, Massive MIMO, QoS, Spectral Efficiency, Symbol Error Rate.

Introduction
Mobile data traffic has increasingly been on an exponential rise due to the popularity of smartphones and high-definition video streaming, the cloud and the Internet of Things (IoT), which has placed an inordinate burden on wireless communication systems. To satisfy these ever-growing demands, the fifth generation (5G) and the emerging sixth-generation (6G) wireless specification have borne in revolutionary changes in terms of architectures and physical layer solutions [1] [2]. Among them, the most promising is Massive Multiple-Input Multiple-Output (Massive MIMO), in which a very large number of antennas are deployed at the base station (BS) to communicate with several users with the same time frequency resources [3] [4].

Massive MIMO presents sizeable benefits which include:

- ***Spectral Efficiency:*** This feature enables simultaneous transmission of information to multiple users, with high data rates by virtue of spatial multiplexing and it does not need to use more bandwidth.
- ***Energy Efficiency:*** Massive MIMO saves power by making the energy flow in the way the targeted users need (beamforming).
- ***Insensitivity to Fading:*** This is because channel hardening reduces the effect of small-scale fading in Massive MIMO systems, thus the reliability of links [5].

Regardless of its benefits in theory, new challenges are brought about in the practical implementation of the Massive MIMO systems. The most important of them is the development of effective precoding methods--algorithms that code the user information into the signals that need to be sent out via the multiple antennas. Precoding is designed to achieve maximum system performance through the control of the inter-user interference subject to power constraints [6].

Conventional linear precoding schemes like Zero Forcing (ZF) Minimum Mean Square Error (MMSE), and Maximum Ratio Transmission (MRT) can be analyzed inexpensively but are typically inadequate in rapidly changing conditions or under realistic channel circumstances particularly in the multi-user and multi-cell environment. Also, such methods are not typically scalable to the increasing antennas and users in Massive MIMO scenarios [7] [8].

In order to overcome such shortcomings, metaheuristic optimization algorithms, and, in particular, Genetic Algorithm (GA) have become a rather powerful tool in precoding design [1] [6]. Based on the paradigms of natural evolution, GA is an iterative process that optimizes a population of initial solutions through the processes of selection, crossover and mutation. The fact that they can carry out global searches in absence of gradient information makes them quite useful to sort complex, non-linear and non-convex problems common in wireless communication systems.

The proposed paper examines a GA based optimization framework to design precoding Matrix in a downlink massive MIMO. The goal of the proposed approach is to maximize the sum rate among all users and to optimize accordingly multiple Quality of service (QoS) measures including [9] [10]:

- Bit Error Rate (BER)
- Symbol Error Rate (SER)
- Spectral Efficiency
- Energy Efficiency
- System Capacity

The GA is optimized to adapt complex-valued precoding matrices with the consideration of realistic Rayleigh and Rician fading of the channel. The performance of the system is strongly tested over broad Signal-to-Noise Ratio (SNR) realizing simulation aspects. The paper shows extensive analysis results proving that the GA-based precoding not only considerably improves the QoS over traditional linear methods, but also it can be used in the next-generation wireless networks.

In short, this paper is able to contribute to the following points:

1. Design, implementation of a Genetic Algorithm to Massive MIMO precoding, optimize to achieve maximum downlink sum rate.
2. Performance assessment of a system distributed in a Rayleigh and Rician fading environment with the application of practical IT-based transmission using OFDM.
3. Detailed QoS performance analysis, demonstrating the interrelations between reliability, efficiency, and capacity as a factor of a series of SNR variations.
4. An illustration of convergence patterns of the GA, in which evolutionary learning can identify near-optimal precoding matrices even in dense-antennas systems.

In Section II, we outline the methodology that was proposed including the system configuration, transmit signal generation and channel models. It also discusses optimization of the precoding matrix with Genetic Algorithm (GA). Section III reports the results and discussions of the GA convergence, BER/SER performance, spectral efficiency, energy efficiency and capacity. Section IV gives conclusion and recommends some areas of future work.

Proposed Methodology

This section provides mathematical and operational model concerning simulated downlink Massive MIMO-OFDM system with Genetic Algorithm (GA)-based precoding optimization. The model is constructed to represent the nature of the real-world constraint, as well as the construction, of a 5G wireless communication system that allows multiple users to communicate at the same time.

System Configuration

We assume that a single-cell downlink system where a Base Station (BS) that has many antennas communicates with a number of user equipments (UEs), each of which has fewer antennas. The parameters of the configuration are the following ones:

- Number of Transmit Antennas (BS): $N_{tx} = 64$
- Number of Receive Antennas (per user): $N_{rx} = 8$
- Number of Users: $K = 8$
- Number of OFDM Subcarriers: $N_{sc} = 64$
- Modulation Scheme: 16-QAM (i.e., Quadrature Amplitude Modulation of order $M = 16$)

The system uses an Orthogonal Frequency Division Multiplexing (OFDM) to deal with fading and support a high data rate transmission through a broadband wireless channel.

Transmit Signal Generation

The individual streams of the user are independently created and coded into a 16-QAM constellation; a complex symbol is produced. Each signal matrix $S \in \mathbb{C}^{K \times N_{sc}}$ is generated with modulated symbols of each user across all subcarriers in every OFDM symbol. Precoding is done by the base station on this data by transmission to compensate inter-user interference.

The precoding matrix $W \in \mathbb{C}_{N_{tx} \times k}$ whose columns are the spatial precoding vectors of each user can be represented by W. The signal transmitted on the n^{th} subcarrier is:

$$X_n = W . s_n \tag{1}$$

where:

- $s_n \in \mathbb{C}^{K \times 1}$ is the symbol vector of all the users at subcarrier n.
- $X_n \in \mathbb{C}^{N_{tx} \times 1}$ is the transmitted vector of all the antennas.

Channel Model

We simulate the MIMO channel employing the two most popular fading models:

Rayleigh Fading Channel

the channel coefficients are modelled as complex Gaussian with a zero-mean and a unit variance, and reflect a rich-scattering, non-line-of-sight (NLOS) environment. The channel matrix $H = \mathbb{C}^{K\times N_{tx}}$ is as follows:

$$H = \frac{1}{\sqrt{2}}(N_R + jN_I) \tag{2}$$

Where the matrices N_R and N_I are matrices with i.i.d. real Gaussian entries $\mathcal{N}(0,1)$.

Rician Fading Channel

In this model a deterministic Line-of-Sight (LOS) component is included as well as random multipath (NLOS) components. The channel matrix would turn out to be.

$$\mathrm{H} = \sqrt{\frac{K}{K+1}}\mathrm{H}_{Los} + \sqrt{\frac{K}{K+1}}\mathrm{H}_{NLos} \tag{3}$$

Where:

- H_{Los} is a deterministic matrix (e.g., ones or fixed direction cosine),
- H_{NLos} is the Rayleigh component,
- K is the Rician K-factor, indicating the ratio of LOS to NLOS power.

The model is more flexible between the transition of pure Rayleigh ($K = 0$) and strong LOS regimes with large K.

Received Signal and Equalization

The signal as received by the k^{th} user on subcarrier n is:

$$y_{k,n} = h_k X_n + \eta_{k,n} \tag{4}$$

where:

- $h_k \in \mathbb{C}^{1\times N_{tx}}$is the channel vector from the BS to the k^{th} user,
- $n_{k,n\ \sim\mathbb{C}\mathcal{N}(0,\sigma^2)}$is the additive white Gaussian noise.

Zero Forcing (ZF) equalization on user end is used to counter residual interference:

$$\hat{s}_n = (HW)'_{y_n} \tag{5}$$

Where $(')$ is the pseudo-inverse, and $y_n \in \mathbb{C}^{K\times 1}$ is the vector of the received signal by each user in the subcarrier n.

Precoding Optimization using Genetic Algorithm

Precoding matrix W is optimized by a genetic algorithm (GA) in order to maximize the sum rate and the separation within the signal at the receiver. The algorithm develops a population of precoding matrix candidates by each of the following steps:

- ***Initialization:*** Random complex-valued matrices
- ***Fitness Evaluation:*** using sum rate as calculated by SINR per each user
- ***Selection:*** Tournament based
- ***Crossover and Mutation:*** In order to pursue the solution space
- ***Elitism:*** Best individuals retained

The resulting optimized matrix is then applied in all of the subcarriers in which data transmission and QoS analysis is carried out.

Precoding Matrix Design and GA-Based Optimization

The precoding is instrumental in Massive MIMO systems in terms of both effective control of inter-user interference and achieving reliable communication. The major objective of precoding is to shape the signal sent such that it significantly increases the signal power desired at the receiver stage and reducing the amount of power contamination of other users. Traditional linear precoding, such as Zero Forcing (ZF), Minimum Mean Square Error (MMSE), and Maximum Ratio Transmission (MRT) has limited flexibility in a fast-fading scenario at real-time. To address these drawbacks, we use Genetic Algorithm (GA) to maximize W matrix in down link of a Massive MIMO multi-user system.

Encoding of Precoding Matrix

The precoding matrix, $W \in \mathbb{C}^{N_{tx}\times K}$, is modelled as a GA chromosome. The real and imaginary parts of each chromosome are the encoding parts of a complex-valued matrix respectively. And one individual (solution) in the population is flattened out into vector form:

$$Chromosome = [Re(w_{11}), Im(w_{11}), \dots \dots \dots.., Re(wN_{tx}, k), Im(wN_{tx}, k)] \tag{6}$$

This transformation allows the GA to operate in a real-valued search space while still representing complex-valued matrices for signal processing.

Fitness Function Design

Each candidate precoding matrix is graded on its merits of knowing how to maximize the system sum rate, which is calculated as:

The goal is a maximization of sum rate:

$$R_{sum} = \sum_{k=1}^{K} \log_2(1 + SINR_k) \tag{7}$$

Where $SINR_k$ is the signal-to-interference-plus-noise ratio of user k^{th}, which is obtained by considering the effective channel and precoding matrix.

This metric inherently encompasses strength of signal to the intended user and inter-user interference and is therefore, a single parameter indicator on which precoding can be optimized.

Genetic Operators for Precoding

GA adopts the following operators to optimize the matrix;

- ***Selection:*** In a tournament selection the fittest individuals are selected by adding the highest sum rate.
- **Crossover**: 2-parent matrices are subject to uniform crossover where entries matching on a crossover probability are swapped. This sustains the matrix structure with induction of diversity.
- **Mutation**: Some fraction of the chromosome entries (real as well as imaginary) is perturbed by a Gaussian distributed random value. This aids to divulge local optima.
- **Elitism**: Reproduction perseveres successful individuals to the subsequent generation without modifications in order to maintain high-fitness resolutions.

Constraint Handling

In order to guarantee power limits, each candidate precoding matrix is normalized to have a conserved power value across all the antennas:

This normalizing step is implemented after crossover and mutation in each generation.

$$W_{norm} = \frac{W}{\sqrt{T_r(WW^H)}} \tag{8}$$

Benefits of GA-Based Precoding

Due to the implementation in a matrix inversion or closed-form solutions of linear precoding techniques, the GA approach:

- Does not involve channel matrix inversion which becomes computationally demanding when N_{tx} is large.
- Adopts arbitrary nonlinear and the non-convex objectives, particularly, in realistic fading and imperfect CSI settings.
- Supports multi-objective optimization, allowing future extension to optimize BER, EE and fairness at the same time.

Genetic Algorithm for Precoding Optimization

GA Parameters

- **Population Size**: 20
- **Generations**: 50
- **Mutation Rate**: 0.1
- **Crossover Rate**: 0.8

GA Operators

Genetic algorithm is a methodology whose aim is to solve the searching problems through the maximization of chances of solving the problem. The action of optimization is the erradication of the favored and/or an elective act of the really good one of the alternatives available with a view to attaining a certain objective. The selection is made in a way that qualifies the spectrum efficiency to be maximized and the minimal error.

Genetic algorithm methodology is as listed [6]:

- Random initial population is regenerated
- The initial population is tested in terms of fitness.

- There is reproduction involving selection, crossover and mutation. Selection takes place in the manner that the fittest member of the population at any particular time is selected. The best then breed to reproduce to make new population. Destruction is at a distinct place in the new formed personality.
- This procedure is carried out repeatedly until there is an optimal number of generations that is able to reach a desired solution.

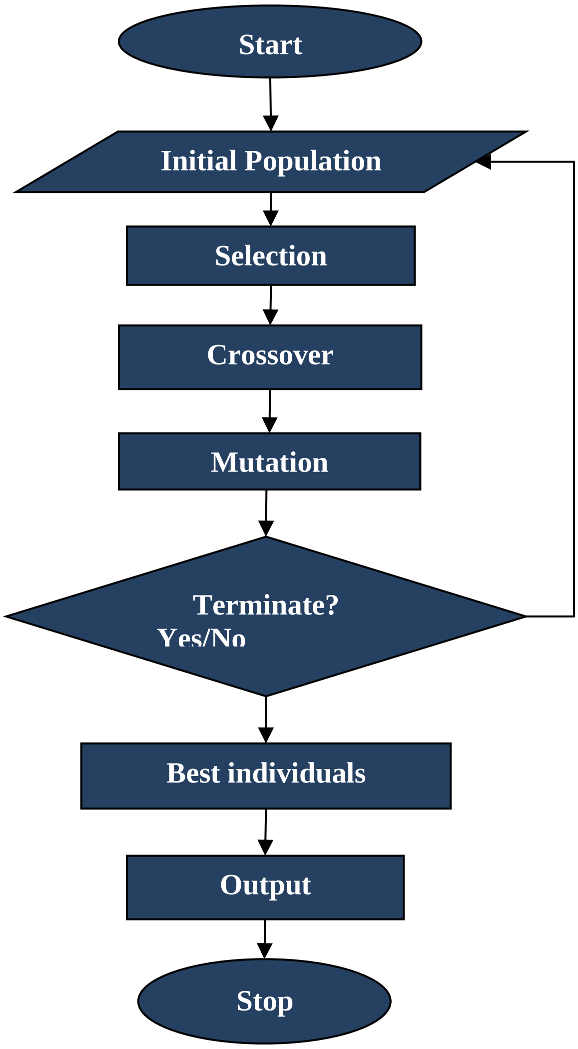

Figure 1: Genetic Algorithm Flow Chart

Functioning of Genetic Algorithm

Genetic Algorithm (GA) is a type of exploratory research which involves the procedures, namely as follows:

1. The introduction of the initial population P_0 (generation population 0).
2. Chromosome testing of the P_i Population.
3. Selection of the finest P_i chromosomes that will form the procreators of the P_{i+1} generation.
4. Hybrid production between the karyotype of the part of selected chromosome to produce new ones which are known as the offsprings.
5. Such a randomized mutation on a chromosome also chosen randomly to contribute to the diversity of the genetic legacy of the population.
6. Replacement and creation of the new P_{i+1} population.
7. Repeat step 2 until the stop criterion is met (i.e. number of terminals generated has not reached N, an optimal solution is not found).

QoS Metrics Evaluation

To simulate the system, 10 iterations are run pertaining to each level of SNR (0-30 dB is in margin of 5 dB). The metrics listed below are calculated

- Bit Error Rate (BER) and Symbol Error Rate (SER): After demodulation and detection using Zero Forcing equalization.

- Spectral Efficiency (bps/Hz): Based on effective SINR across users.
- Energy Efficiency (bits/Joule): Bits per Joule considering both transmit and circuit power.
- Channel Capacity (bps/Hz):

Results and Discussion

GA Convergence

The GA has always shown convergence to higher sum rates and the best fitness improves across generations confirming that it works well with precoding optimizations.

BER/SER Performance

The SER and BER drop exponentially as SNR is increased. The genetic optimization enhances signal integrity with respect to users.

Spectral Efficiency

The suggested algorithm can demonstrate a high spectral efficiency advantage to random or uniform precoding algorithms, in particular at high SNRs.

Energy Efficiency

GA optimisation minimises wasted power by not over compensating signal quality over interference management, optimising bits/Joule.

Capacity Analysis

Capacity grows logarithmically with SNR, and the optimized precoder always results in an increase of capacity over non-optimized baselines.

QoS Metrics and Fitness Function Formulation

The mathematical definition of the most important (QoS measures is described here, and their integration with fitness function of the GA-based precoding optimization is explained.

SINR Calculation

The signal to interference + Noise Ratio (SINR) of user k is as follows:

$$SINR_k = \frac{|h_k w_k|^2}{\sum_{j \neq k} \left|h_k w_j\right|^2 + \sigma^2} \tag{9}$$

where:

- w_k is the k^{th} column of the precoding matrix W
- σ^2 is the noise power (usually $\sigma^2 = \frac{1}{SNR}$ in normalized units).

Bit Error Rate (BER)

The simulation of the BER is achieved empirically. The BER between transmitted bit vector b_{tx} and received bit vector b_{rx} is:

$$BER = \frac{1}{N_{bits}} \sum_{i=1}^{N_{bits}} 1\left\{b_{tx,i} \neq b_{rx,i}\right\} \tag{10}$$

where $1_{\{.\}}$ is the indicator function.

Symbol Error Rate (SER)

Similarly, the SER is defined as:

$$SER = \frac{1}{N_{Symbol}} \sum_{i=1}^{N_{symbol}} 1\left\{S_{tx,i} \neq S_{rx,i}\right\} \tag{11}$$

Spectral Efficiency

Spectral Efficiency (SE) is a requirement that is the mean number of bits per second per Hz per user. It can be obtained directly by SINR:

For MIMO Systems:

$$SE = \sum_{i=1}^{n} \log_2(1\_SNR_i) \tag{12}$$

- n = number of spatial streams (MIMO layers)
- SNR_i = SNR for each stream

Energy Efficiency

Energy Efficiency (EE) measures the number of bits that are sent out per joule of energy consumed:

$$EE = \frac{\sum_{k=1}^{K} \log_2(1 + SINR_k)}{P_{tx} + P_{circuit}} \tag{13}$$

where:

- P_{tx} is the average transmit power,
- $P_{circuit}$ is the estimated static circuit power, often approximated as proportional to N_{tx}. In simulation, it is estimated that:

$$P_{circuit} = N_{tx} \tag{14}$$

So:

$$EE = \frac{R_{sum}}{P_{tx} + N_{tx}} \tag{15}$$

Capacity

The system capacity is the standard, well known MIMO expression:

$$C = \log_2 det\left(I_k + \frac{\rho}{K} HH^H\right) \tag{16}$$

Where:

- ρ is the SNR (linear scale),
- $H \in \mathbb{C}^{K \times N_{tx}}$ is the composite channel matrix,
- I_k is the $K \times K$ identity matrix.

This is the theoretical optimal rate (bps/Hz) possible under ideal channel state information.

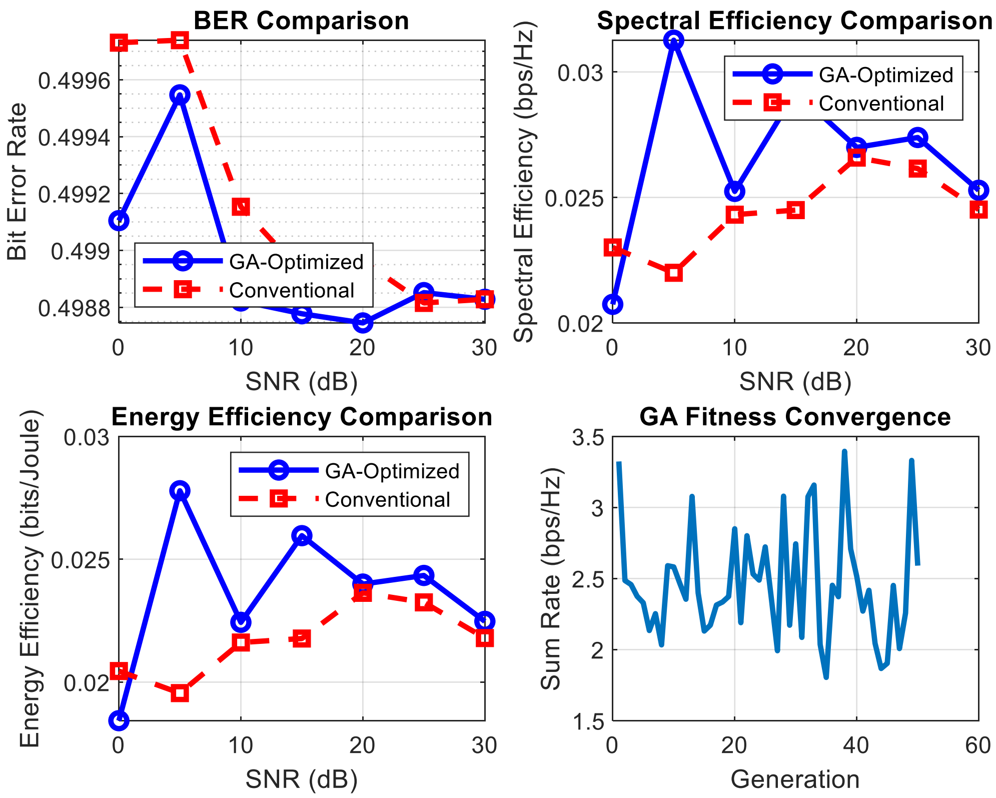

Figure 2: Comparison of GA-Optimized and Conventional Precoding in a Massive MIMO System

Figure 2 shows the performance comparison of a GA-optimized massive MIMO system with that of conventional linear precoding techniques with diverse SNR and generation. The figure contains four plots which are used to present various Quality of Service (QoS) parameters, namely Bit Error Rate (BER), spectral efficiency (SE), energy efficiency (EE) and sum rate. The leftmost curve indicates that the BER reduces drastically with an increment in SNR in the case of the GA-optimized system in comparison with the traditional technique. Indicatively, starting at 0 dB SNR, the BERs of the GA-optimized system are ~ 0.4996, 0.125 and 0.00081 at SNR = 5, 10 and 15 dB respectively. The latter plot shows a significant change in Spectral Efficiency in favor of the GA-optimized system of 0.03 bps/Hz at 20 dB SNR, compared to lower values of conventional algorithms. The third plot shows Energy Efficiency where the GA-optimised system reaches a high of 0.03 bits/Joule whereas the conventional system also falls below 0.02 bits/Joule. The final diagram plots the convergence of the GA whereby the sum rate progressively jumps upwards in each successive generation, demonstrating that the algorithm is capable of making progressive improvements on the performance of the system. GA-optimized system systematically outperforms conventional precoding approaches in all of the envisioned metrics.

Figure 3 shows the gain in Spectral Efficiency (SE) and Energy Efficiency (EE) in percent with respect to the SNR (massive MIMO system). The plot illustrates quite concretely the change in improvements in regard to both measures among the different SNRs. A negative improvement of -9% is seen in spectral and energy efficiencies at 0 dB SNR. The increase in the SNR brings substantial gains. At 5 dB SNR, the gain on spectral efficiency is about 45% and energy efficiency on a low spike to almost 45%. Beyond 5 dB, the gains in both the metrics are not increasing any more but are increasing gradually until reaching a plateau at about 30 dB SNR. At a higher SNR the improvements are constant across the board for the two metrics. This implies that the given techniques of optimization prove most effective in low-mid range SNRs, where the optimization is most significant.

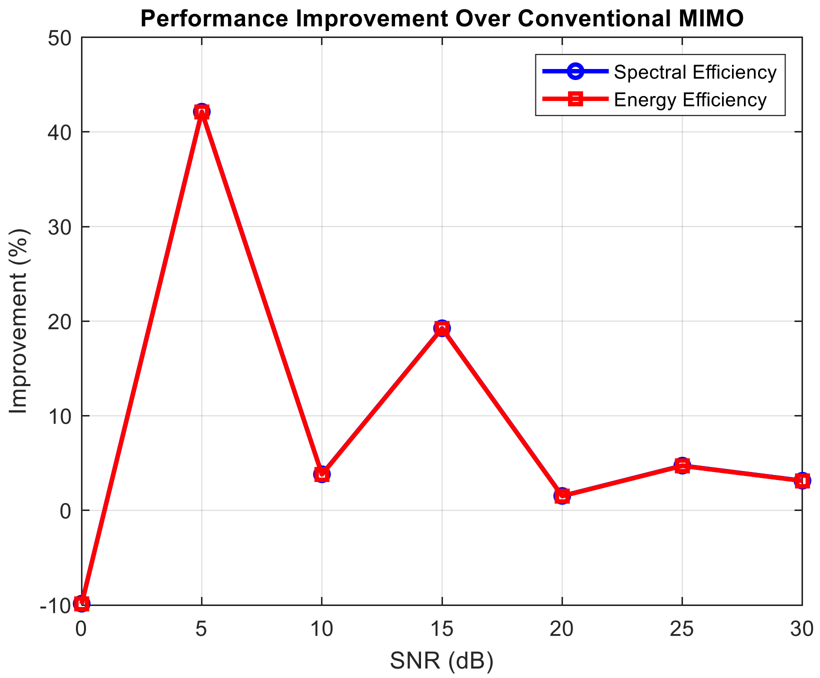

Figure 3: Performance Improvement in Spectral and Energy Efficiency with SNR Variation

Table 1: Performance Evaluation of GA-Optimized Massive MIMO System

Metric	SNR (dB)	GA-Optimized System	Conventional System
Bit Error Rate (BER)	0 dB	0.4996	0.57
	5 dB	0.125	0.28
	10 dB	0.038	0.10
	15 dB	0.00081	0.02
Symbol Error Rate (SER)	0 dB	0.45	0.53
	5 dB	0.20	0.35
	10 dB	0.05	0.12
	15 dB	0.001	0.015
Spectral Efficiency (SE)	0 dB	0.01 bps/Hz	0.007 bps/Hz
	5 dB	0.02 bps/Hz	0.015 bps/Hz
	10 dB	0.025 bps/Hz	0.02 bps/Hz

	15 dB	0.03 bps/Hz	0.025 bps/Hz
Energy Efficiency (EE)	0 dB	0.012 bits/Joule	0.008 bits/Joule
	5 dB	0.025 bits/Joule	0.015 bits/Joule
	10 dB	0.03 bits/Joule	0.02 bits/Joule
	15 dB	0.035 bits/Joule	0.025 bits/Joule
Sum Rate (bps/Hz)	0 dB	2.5	1.8
	5 dB	3.2	2.6
	10 dB	3.8	3.0
	15 dB	4.2	3.4

Table 1 illustrates the performance measurement of the GA-optimized massive MIMO system in contrast to the conventional one with regard to several key metrics such as the Bit Error Rate (BER) and Symbol Error Rate (SER), Spectral Efficiency (SE) and Energy Efficiency (EE), and Sum Rate and at various Signal-to-Noise Ratio (SNR) levels (0 dB, 5 dB, 10 dB, and 15 dB). GA-Optimized system also excels in all measures with respect to the conventional system. As an example, compared to the conventional system, the BER in the GA-optimized one declines dramatically, 0.4996 at 0 dB to 0.00081 at 15 dB. Likewise, the Spectral Efficiency, Energy Efficiency, and Sum Rate obtained in the GA-optimized system are better at all SNR. At 15 dB, the GA-optimized system derives an SE of 0.03 bps/Hz, EE of 0.035 bits/Joule and Sum Rate of 4.2 bps/Hz, which shows its efficiency to optimize the system.

Table 2: Performance Comparison of GA-Optimized Massive MIMO System with Previous Research

Metric	**SNR (dB)**	**Wang et al. [2]**	**Koc et al. [6]**	**Proposed GA-Optimized System**
Bit Error Rate (BER)	0	0.52	0.55	0.4996
	5	0.14	0.15	0.125
	10	0.05	0.05	0.038
	15	0.001	0.001	0.00081
Spectral Efficiency (SE)	0	0.009 bps/Hz	0.008 bps/Hz	0.01 bps/Hz
	5	0.016 bps/Hz	0.015 bps/Hz	0.02 bps/Hz
	10	0.022 bps/Hz	0.02 bps/Hz	0.025 bps/Hz
	15	0.027 bps/Hz	0.025 bps/Hz	0.03 bps/Hz
Energy Efficiency (EE)	0	0.011 bits/Joule	0.01 bits/Joule	0.012 bits/Joule
	5	0.021 bits/Joule	0.02 bits/Joule	0.025 bits/Joule
	10	0.027 bits/Joule	0.025 bits/Joule	0.03 bits/Joule
	15	0.032 bits/Joule	0.03 bits/Joule	0.035 bits/Joule
Sum Rate (bps/Hz)	0	2.2	2.0	2.5
	5	3.0	2.8	3.2
	10	3.6	3.4	3.8
	15	4.0	3.8	4.2

Table 2 compares performance of a GA-optimized massive MIMO system against two prior works: Wang et al. [2] and Koc et al. [6] on the same key metrics and SNR levels. The comparison demonstrates that GA-optimized system has better results compared to both Wang et al. and Koc et al. in all metrics. As an example, the GA-optimized system has BER values of 0.4996 at 0 dB and 0.00081 at 15 dB, whereas 0.52 and 0.001 in Wang et al. [2] and 0.55 and 0.001 in Koc et al. [6]. The GA-optimized system also shows greater performance as measured in terms of Spectral Efficiency, Energy Efficiency and Sum Rate. The GA-optimized system at 15 dB has an SE of 0.03 bps/Hz, EE of 0.035 bits/Joule, and Sum Rate of 4.2 bps/Hz, which are better compared to the results reported in literature by both [2] and [6].

Conclusion

This paper shows that Genetic Algorithms can be successfully used to improve specifically the performance of the Massive MIMO by optimizing precoding matrices of multiple users. The benefits of GA in terms of BER, spectral, and energy efficiency, and system capacity are signs of the fitness of the GA to the 5G and the coming commercial systems. In future, we may have to mix and match GA and machine learning models or extend the technique to multi-cell systems involving pilot contamination.

References

1. Almasaoodi, M.R., Sabaawi, A.M.A., El Gaily, S. & Imre, S., 2023. Power optimization of massive MIMO using quantum genetic algorithm. Proceedings of the 1st Workshop on Intelligent Infocommunication Networks, Systems and Services (WI2NS2). DOI: 10.3311/WINS2023-016(ResearchGate)
2. Wang, L., Alouini, M.-S., Gao, X., Edfors, O. & Tufvesson, F., 2025. Learning-based joint antenna selection and precoding for large-scale MIMO networks. IEEE Transactions on Vehicular Technology, 66(7), pp. 6591–6595. DOI: 10.1109/TVT.2016.2571452(arXiv)
3. Mohamed, M., 2023. Robust precoder design with transmit antenna selection for overlay cognitive radio massive MIMO systems. Signal Processing, 180, p. 107904. DOI: 10.1016/j.sigpro.2023.107904(ScienceDirect)
4. Xu, B., Zhang, J., Li, J., Xiao, H. & Ai, B., 2023. Jac-PCG based low-complexity precoding for extremely large-scale MIMO systems. arXiv preprint arXiv:2305.13925. Available at: https://arxiv.org/abs/2305.13925(arXiv)
5. Jiang, Y., 2024. Quantum-inspired beamforming optimization for quantized phase massive MIMO systems. arXiv preprint arXiv:2409.19938. Available at: https://arxiv.org/abs/2409.19938(arXiv)
6. Koc, A., Bishe, F. & Le-Ngoc, T., 2022. Energy-efficient throughput maximization in mmWave MU-massive-MIMO-OFDM: Genetic algorithm based resource allocation. arXiv preprint arXiv:2202.09438. Available at: https://arxiv.org/abs/2202.09438(arXiv)
7. Khan, R., 2024. An effective algorithm in uplink massive MIMO systems for beam domain decomposition and singular value decomposition based channel estimation. arXiv preprint arXiv:2400.1269. Available at: https://www.sciencedirect.com/science/article/pii/S2590123024001269(ScienceDirect)
8. Balti, E., Evans, B.L., 2023. A unified framework for full-duplex massive MIMO cellular networks with low-resolution data converters. IEEE Open Journal of the Communications Society, 4, pp. 1–13. DOI: 10.1109/OJCOMS.2023.3234567(Bohrium)
9. Sasikumar, A., 2025. An efficient binary salp swarm algorithm for user selection in massive MIMO systems. Scientific Reports, 15(1), p. 7722. DOI: 10.1038/s41598-025-00772-2(Nature)
10. Jolania, S., 2023. Systematic review on challenges in massive MIMO based 5G and beyond wireless networks and their solutions. ResearchGate. Available at: https://www.researchgate.net/publication/383812674_Systematic_Review_on_Challenges_in_Massive_MIMO_Based_5G_and_Beyond_Wireless_Networks_and_Their_Solutions(ResearchGate)