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Original Article

A PSO-Optimized Non-Linear Channel Capacity Enhancement Framework for CSI-based and MIMO Wireless Communications

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Abstract *- Optimization of channel capacity in Channel State Information (CSI)-assisted Multiple-Input Multiple-Output (MIMO) systems is a critical need for beyond 5G and future 6G wireless communication systems, in which non-linear propagation and time-varying fading channels significantly affect the channel capacity. Traditional approaches based on linear channel models and complex optimization algorithms often face challenges in terms of robustness, Scalability, and global optimality. To overcome these limitations, this study proposes a Particle Swarm Optimization (PSO)-optimized non-linear channel capacity enhancement scheme by incorporating Monte Carlo-based stochastic channel modeling, polynomial analysis of Signal-to-Noise Ratio (SNR)-capacity trends using K-fold cross-validation, and evolutionary optimization. Simulations performed in a realistic fading channel environment strongly validate the existence of a strong non-linear SNR-capacity trend and statistical channel stability. The baseline Monte Carlo simulation model establishes a channel capacity prediction of approximately 1.3×10^8 bps when operating at an SNR value of 20 dB. The PSO-optimized approach results in a channel capacity increase to 3.79×10^8 bps, representing an approximately 2.91-fold increase over the baseline system. The proposed scheme demonstrates superior performance through simulation tests against Single Input Single Output (SISO), Single Input Multiple Output (SIMO), Multiple Input Single Output (MISO), and CSI-assisted MIMO systems, which prove its effectiveness for future high-capacity wireless communication systems to achieve maximum channel capacity.*

Keywords *- MIMO wireless communications, Channel capacity optimization, Particle swarm optimization, Monte Carlo simulation, Non-linear channel modeling, 6G networks.*

1. Introduction

Wireless communications have experienced rapid growth in recent years, as reflected in the exponential increase in both global mobile connectivity and the number of smart devices and bandwidth-intensive applications [1, 2]. As a result, researchers and leaders in the industry are under tremendous pressure to develop communication systems that can meet not only current societal demands for throughput, efficiency, and reliability, but also exceed the traditional expectations [3-5]. The capacity of a channel is one of the primary ways to assess the efficiency of a communication system, and it represents the theoretical data rate at which information can be sent with very low error rates [6]. Therefore, increasing the capacity of channels has become one of the key areas of focus within the field of wireless communication, specifically advanced communication systems using MIMO technology [7-9].

The ability of MIMO systems to take advantage of spatial diversity and permit simultaneous parallel data transmissions is well documented in many research studies as a method of improving throughput and spectral efficiency [10, 11]. When combined with knowledge of the channel state, MIMO systems can also adaptively change the parameters of their transmissions to enhance the probability of successful transmission of the correct data. One of the major challenges is the extreme nonlinearity of wireless channels in a non-ideal environment [11, 12]. Other factors, such as multipath fading, shadowing, mobility, and interference, create a large amount of uncertainty in how a signal can propagate in the wireless medium. These channel characteristics make reliable channel-capacity estimation and optimization challenging, particularly when the SNR–capacity relationship is nonlinear and channel conditions vary stochastically [13-16].

One of the key shortcomings of existing works is reliance on idealized linear channel models, which are inadequate in representing the complexity and randomness of a realistic wireless communication scenario [17, 18]. Besides, several

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optimization frameworks for capacity improvement bear a high computational cost and often rely upon gradient information, which might not be available or necessarily accurate in highly varying channel conditions [19]. These limitations indicate the need for a framework that can represent stochastic channel behaviour, characterize nonlinear SNR–capacity relationships, and perform capacity optimization without relying exclusively on gradient-based procedures.

Within this context, different ways to enhance channel capacity are considered. These include channel modelling and flexible channel-based transmission [20, 21]. Transmitting at a flexible rate with regard to the assumption on the channel can improve the spectral efficiency. Gradient-based methods as well as metaheuristic methods are used for optimization. Of the metaheuristic methods, Particle Swarm Optimization (PSO) has been used to address problems in resource allocation in wireless communications, adaptive antenna system configuration, and wireless channel estimation and signal quality assessment. Furthermore, recent studies focus on the use of models that combine intelligent and learning-based techniques to develop methods and systems that go beyond the existing methods and systems in the field [22-24].

The current work provides a comprehensive overview of previous research studies that have investigated PSO-based solutions that optimize non-linear channel capacity and MIMO wireless transmission systems. In 2025, Zhong et al. [25] developed the Two-Dimensional Pinching-Antenna System (2D-PASS), which transformed the standard line-shaped dielectric waveguide into a flexible circuit design. The system used PSO to enable users to control their beamforming system through both continuous and discrete antenna location options. The 2D-PASS system demonstrated a minimum SNR enhancement that exceeded 40% when compared to both fixed-position and line-based PASS systems across different user equipment distribution scenarios. Xu et al. (2026) [26] reviewed fluid antenna-assisted non-terrestrial networks for 6G and beyond, discussing their fundamental principles, system architectures, channel characteristics, and recent developments. The study highlighted the potential of fluid antenna technologies for improving spatial adaptability and supporting reliable communication in dynamic and rapidly changing wireless environments. In the same year, Chukwudi et al. (2025) [27] introduced an Adaptive PSO–Dynamic Power Allocation (APSO-DPA) framework for downlink NOMA systems with imperfect CSI, targeting simultaneous optimization of energy efficiency, user fairness, and robustness. The reported results state that at an SNR of 40 dB, the peak sum rate was 17.7367 bps/Hz, and the energy efficiency was 0.00177 bits per joule with a Jain's Fairness Index of 0.5971. 2025A1. In the same way, Han et al. (2025) [28] created a compressed sensing-based adaptive channel estimation algorithm for semi-passive IRS systems that did not require prior knowledge of the number of paths and further refined active sensor placement with PSO. The simulations reported a 25% lower overhead of pilots with equal estimation accuracy, and a PSO-based placement of sensors that improved Mean Squared Error (MSE) as much as 2.5 dB over the random and uniform placements. El-Shorbagy et al. (2024) [29] proposed several improved variants, hybrid, discrete, and multi-objective versions of the Henry Gas Solubility Optimization (HGSO) algorithm. The results showed that HGSO was self-explanatory for HGSO, as it first passed all the benchmark tests with a mean rank of 1.33.

Jameer Basha et al. (2023) [30] proposed a hybrid architecture integrated with Partial Transmit Sequence (PTS) optimized using PSO and Deep Belief Network (DBNet) for 5G-OFDM systems. This architecture achieved a 7.7 dB reduction and improved performance with low BER and low signal distortion. Sharma and Grewal (2023) [31] proposed an FSO communication system turbulence and pointing error control scheme, an optimized packet length using PSO, and a packet length gain improvement of 0.4 dB to 1.8 dB. Cao et al. (2022) [32] proposed an IRS-assisted MIMO system with rapidly changing channels, using a statistical average over a longer timescale for slower optimization over IRS configuration. Model-based PSO and mini-batch PSO techniques diminished optimization overhead while improving the Average Achievable Rate (AAR) by as much as 27.6%. Turan and Coleri (2021) [33] proposed another study employing machine learning techniques for channel modelling in the context of Vehicular Visible Light Communication (VVLC) and used a Multilayer Perceptron (MLP) approach. The model achieved the best channel loss prediction accuracy with a Root Mean Square Error (RMSE) of 3.53 dB, outperforming traditional curve-fitting models, which yielded an RMSE of 7 dB. In 2020, Asadullah et al. [34] introduced the FLeCSI algorithm, a fuzzy logic-empowered cognitive and social information-based PSO variant for blind channel and data estimation in MIMO-OFDMA systems. This method outperformed other PSO variants like FLOMPSO and TOMPSO by achieving significantly lower MMSE and BER ($1.5017 \times 10{-}6.6$) in multi-user detection scenarios. Collectively, these studies utilize evolutionary techniques and statistical or machine learning models to resolve multiple challenges in wireless communication. However, most of them improve signal quality, perform channel estimation, allocate communication resources, or predict channel loss. Few studies have incorporated an integration of non-linear SNR- capacity models with statistical verification and PSO for capacity enhancement in a MIMO system with CSI.

Despite the progress reported in PSO-based wireless communication research, an important methodological gap remains in the specific integration of channel simulation, nonlinear capacity modelling, statistical validation, and global optimization. PSO has been utilized in wireless communications for antenna and beamforming optimization [25, 26], resource allocation with imperfect CSI [27], adaptive

channel estimation and sensor deployment [28], IRS-based MIMO optimization in fast-varying channels [32], and channel/data estimation in MIMO-OFDMA [34]. Thus, the applicability of PSO for wireless communications tasks such as signal-quality enhancement, resource allocation, channel estimation, and transmission optimization was illustrated. The specific combination of Monte Carlo-based simulation of the stochastic fading channel, nonlinear polynomial SNR-capacity modelling, K-fold cross-validation, and global PSO-based capacity optimization in the CSI-assisted MIMO system was not sufficiently explored. In particular, the systematic connection between statistically generated channel-capacity observations, a validated nonlinear SNR–capacity model, and subsequent global optimization has received comparatively limited attention in the context considered in this study [25-28, 32, 34].

The problem addressed in this study is about the reliable estimation and optimization of channel capacity in a stochastic and nonlinear fading channel. The random channel realization could lead to fluctuations in the channel capacity, whereas the oversimplified approximation of the SNR-Capacity relation would fail to represent the nonlinearity needed for optimization. Consequently, a methodology needs to be devised that would allow statistical channel realization, channel capacity estimation at varying SNR, modelling the nonlinear relation between SNR and Capacity, verification of the developed predictive model, and selection of the operating point having increased channel capacity.

To address the identified gap, this research work proposes a PSO-based non-linear capacity-enhancing framework for CSI-enabled MIMO wireless communications. This framework consists of various methodologies such as Monte Carlo Stochastic channel simulation, Shannon channel capacity computation, Polynomial modelling of the non-linear relationship between SNR and channel capacity, K-fold cross-validation, and PSO-based global optimization. The Monte Carlo stochastic channel simulation is used to model the variations in the fading channel; Polynomial modeling is used to model the non-linear relationship between SNR and channel capacity.

The novelty of the suggested framework is the particular combination of four elements of the process – stochastic channel simulation, nonlinear SNR-to-capacity modeling, statistical cross-validation, and PSO optimization of CSI-enabled MIMO channels. Prior research typically uses PSO algorithms for particular wireless optimization problems – antenna placement, channel estimation, power allocation, signal quality improvement, or IRS optimization [25-34]. The proposed research suggests the implementation of a particular sequential process, where stochastic channel capacities are simulated using Monte Carlo, the non-linear SNR-to-capacity relationship is modeled using polynomials, cross-validation of K-folds is performed, and then the PSO algorithm is used to perform the capacity optimization. Therefore, the novelty is due to the particular combination of the elements mentioned and their utilization to enhance non-linear SNR-to-capacity relationships rather than the individual application of the existing methods.

The key contributions of the present work are outlined as follows:

- Developed a unified non-linear channel-capacity enhancement framework integrating Monte Carlo simulation, polynomial trend modeling, K-fold CV, and PSO-based optimization.
- Proposed a statistically robust SNR–capacity estimation mechanism capable of capturing realistic non-linear fading-channel characteristics in CSI-assisted MIMO systems.
- Designed a PSO-driven global optimization strategy for maximizing channel capacity under dynamic wireless channel conditions without relying on gradient-based optimization methods.
- Established a polynomial regression-based predictive modeling approach for continuous SNR–capacity trend approximation and optimization guidance.
- Performed extensive comparative analysis against conventional CSI-assisted MIMO systems under identical SNR conditions.
- Demonstrated significant channel-capacity enhancement, where the optimized framework achieved approximately threefold improvement compared to the baseline Monte Carlo simulation model at 20 dB SNR.

The remaining part of the paper has been organized in such a manner that Section 2 defines the proposed methodology, including the structure of the entire framework, the tools, and the functions. Section 3 discusses the results, and Section 4 shows the conclusions and future scope.

2. Research Methodology

This section describes the complete process that was used to estimate non-linear channel capacity and optimize systems through PSO in CSI-supported MIMO wireless communication networks. The suggested framework uses Monte Carlo stochastic channel simulation together with polynomial trend modeling, K-fold statistical validation, and PSO to improve channel capacity in actual fading channel conditions.

2.1. System Parameters Definitions

2.1.1. Bandwidth (B)

Bandwidth is the range of frequency allocated for communication, which is measured in Hertz (Hz) [36]. It indicates the maximum data rate that can be sent across the channel. Increasing bandwidth permits higher capacity, all other parameters held constant. In this methodology, this bandwidth is pre-set and kept fixed during the simulations so as to isolate only the change in SNR value.

2.1.2. SNR Range

The SNR limits indicate how a wireless channel should perform during operation by defining the ratio between signal power and noise power over a given range of values [36]. The SNR is first expressed in Decibels (dB); the SNR is used as a control variable during the simulation to demonstrate the effect of changing the SNR on the available channel capacity. The availability of a wider SNR range can give the best assessment of the overall efficacy of the model at both low and high interference levels.

2.1.3. Shannon Capacity Model

The Shannon Capacity equation establishes the theoretical maximum data rate for a transmission channel under optimal conditions, as shown below [37, 38]:

$$C = B \cdot \log_2(1 + \text{SNR}_{\text{linear}}) \quad (1)$$

Where C represents the channel capacity, B represents the bandwidth, and $\text{SNR}_{\text{linear}}$ denotes the SNR on a linear scale. The capacity equation provided assumes the existence of an Additive White Gaussian Noise Channel (AWGN), which allows for the determination of Capacity Values for all the SNRs used later in the simulation. Establishing these parameters at the outset provides a consistent and effective method to analyze and enhance the performance of Wireless Channels.

2.1.4. Simulation Environment and Parameters

The researchers used MATLAB R2024a with its Communications Toolbox and Optimization Toolbox to build their research framework, which enables simulation, modeling, validation, and optimization tasks. MATLAB was chosen because it provides exceptional numerical computing power, which enables efficient wireless communication analysis, stochastic simulation, and optimization algorithm evaluation.

The Communications Toolbox was used to create CSI-assisted MIMO wireless communication system models, which generated Rayleigh fading channel simulations, produced AWGN test environments, and showed channel capacity results based on different SNR values.

The Optimization Toolbox was used to build the PSO channel capacity enhancement system that performs iterative optimization, convergence assessment, and global search space investigation to find the best operating points for maximum channel capacity.

MATLAB curve-fitting and statistical-analysis functions enabled researchers to implement polynomial trend analysis and K-fold CV to examine the non-linear SNR ratio–capacity connection while assessing model correctness and validation consistency. Table 1 below presents the simulations and optimization settings employed in this technique.

Table 1. Simulation and optimization parameters used in this study

Parameter	Value
Bandwidth	20 MHz
SNR Range	0–20 dB
Channel Model	Rayleigh Fading
Monte Carlo Iterations	1000
Polynomial Degree	2 (Quadratic)
K-Fold Value	5
Number of PSO Particles	30
Maximum PSO Iterations	100
Inertia Weight (w)	0.7
Cognitive Coefficient (c1)	1.5
Social Coefficient (c2)	1.5

2.2. SNR Pre-Processing

In this stage, the designated SNR range (decibels) must be transformed into its linear scale equivalent so that it can be utilized directly in Shannon's capacity formula. This step is very important because one cannot use a logarithmic (dB) number in mathematical expressions involving the ratio of power in the channel to determine channel capacity. The conversion is done using the following standard formula:

$$\text{SNR}_{\text{linear}} = 10^{\left(\frac{\text{SNR}_{\text{dB}}}{10}\right)} \quad (2)$$

Where:

- SNR_{dB} is the SNR in decibels,
- $\text{SNR}_{\text{linear}}$ is the SNR in linear scale (unitless).

The conversion allows the channel simulation engine, particularly the Monte Carlo Simulation Framework, to utilize the linear SNR values from the Shannon model in calculating the capacity of the channel. Once the linear SNR values have been created in both their linear and Decibel (dB) forms, the linear SNR values are used repeatedly throughout the next stages of simulating and assessing the operation of the communication channel in different noise and signal environments.

2.3. Monte Carlo Framework

Monte Carlo Simulation Framework [39, 40] is a statistical approach to modeling and analyzing a complex system. Wireless communications use the Monte Carlo Simulation Framework when estimating channel capacity by using many random sample dimensions to provide an average number of channels that would be encountered in reality, reflecting real-world stochasticity [41, 42]. The proposed methodology incorporates the Monte Carlo Simulation Framework as an important aspect of estimating channel capacity of wireless channels, reflecting realistic stochastic conditions of each wireless channel. As part of this framework, for each pre-specified Signal-to-Noise Ratio (SNR) value, multiple random channel realizations are generated (typically based upon the complex Gaussian or Rayleigh distribution to represent the multipath effects of

wireless communications). Each of these realizations represents the state of the wireless channel at a specific moment in time. Finally, for each simulated channel gain $|h|^2$ Instantaneous capacity is calculated using the modified Shannon capacity formula. The instantaneous capacity is determined from multiple iterations (e.g., 1000 simulations per SNR value) to verify the statistical validity of the channel. For every SNR value considered in this study, the capacity values generated from each experimental run can be averaged together to create a mean channel capacity along with a standard deviation associated with the resulting average MCC. This statistical representation of how the channel behaves represents the sample size on which the results of simulations are based, giving a more accurate perspective of the simulations for any case.

2.3.1. Dataset Generation and Preparation

The study used a dataset that was created through synthetic generation, which employed Monte Carlo-based stochastic wireless channel simulations to simulate Rayleigh fading wireless channels. The researchers created 1000 independent channel realizations for each SNR value, which ranged from 0 to 20 dB, to reproduce authentic wireless channel behavior. The dataset included SNR values and instantaneous channel gains together with channel-capacity measurements derived from Shannon's capacity equation. The researchers used the generated samples to perform three tasks: they created polynomial trend models, executed K-fold CV, and conducted PSO-based optimization.

2.4. Shannon Capacity Formulae for Channel Capacity Computation:

Using the Shannon capacity equation [43] represents the theoretical maximum achievable bit rate of a transmission path without error and in perfect correlation (ideal conditions) [44]. For each SNR level simulated, the statistical aggregation results are used to summarize which SNR provided the maximum amount of channel capacity over time for that specific sample space [45]. The average channel capacity ($\bar{C}$) over time is determined as follows:

$$\bar{C} = \frac{1}{N}\sum_{i=1}^{N} C_i \qquad (3)$$

And the standard deviation [46] σ_C, which measures the variability of capacity due to channel randomness, is computed as:

$$\sigma_C = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(C_i - \bar{C})^2} \qquad (4)$$

Where N is the number of simulation iterations, and C_i represents the capacity of the i^{th} iteration. This step ensures a statistically reliable estimate of channel performance under varying conditions.

The channel-capacity estimation framework was created to operate under specified assumptions and boundary conditions that enable consistent simulation results and optimization research. The study assumes a flat Rayleigh fading wireless communication channel with AWGN. The system operates under the condition that perfect CSI and ideal synchronization between the transmitter and receiver exist during all simulation and optimization activities. The experiments maintain a constant bandwidth to study how different SNR levels impact channel capacity. The channel gains are modeled as statistically independent stochastic processes, which the Monte Carlo simulation framework generates through its randomization method.

The simulations were conducted under fixed bandwidth conditions between 0 and 20 dB SNR operating ranges. The researchers conducted 1000 Monte Carlo channel realizations at each SNR level to achieve statistical consistency. The PSO optimization process operated inside predefined SNR limits and channel-capacity boundaries. The study excluded hardware impairments, antenna coupling effects, and mobility-induced Doppler shifts and thermal-noise variations beyond the AWGN assumption.

2.5. Trend Analysis

Trend Analysis is the process of determining and modelling how SNR interacts with mean channel capacity. The purpose of fitting a smooth curve using typical polynomial regression on the simulation data is to determine the non-linear growth of channel capacity as SNR increases. Trend Analysis allows the mathematical representation of the average channel capacity as a function of SNR, which allows for easier interpretation and prediction of system functionality, as well as for further optimization of system performance [47].

Trend analysis captures the relationship between SNR and mean channel capacity by fitting multivariate data using polynomial regression and non-linear regression techniques. With the mean channel capacities calculated for each SNR value, this trend analysis can also provide insight into other patterns or relationships that might exist from the individual mean channel capacity data points for each SNR value.

The polynomial regression model [48] is generally asecond- or third-degree polynomial that provides a fitted curve correlating SNR (the independent variable) to its mean channel capacity (the dependent variable). To fit the curve, the polynomial regression model is as follows:

$$C(SNR) = a_0 + a_1 \cdot x + a_2 \cdot x^2 + \cdots + a_n \cdot x^n \qquad (5)$$

Where $C(SNR)$ is the predicted capacity as a function of SNR (SNR is usually measured in dB or on a linear scale), and $a_0, a_1, \ldots, a_n$ are the coefficients that are determined from the least squares fitting process.

The result of this step is that simulation results that are generated as discrete data points are converted into a continuous predictive polynomial model that represents the non-linear capacity growth with increasing SNR. This continuous predictive model simplifies any future optimization requirements and allows for a visual representation of trends in system performance throughout real-world deployment phases.

2.6. K-Fold Cross-Validation

K-fold CV serves as a statistical validation method that assesses the predictive model performance and its ability to generalize to new data [49]. The method requires K equal parts of the dataset, where K-1 parts become training material for model development, while the last part serves as validation data. The process conducts K iterations, which are used in every subset for testing purposes. At the same time, the complete results from all parts are averaged to determine final testing outcomes, which help combat overfitting and strengthen model performance. The framework used K-fold CV to assess the SNR-capacity estimation polynomial trend-analysis model, which the authors created through analysis of SNR data and corresponding average channel capacity measurement results. The research employed a 5-fold CV method, which involved dividing the dataset into five equal parts. The study employed four subsets during each training session, while the last subset functioned as validation material to assess how well the polynomial regression model performed with unfamiliar data. The validation process assessed prediction reliability through measurement of prediction consistency and prediction variations across different testing groups, which established the statistical reliability and core strength and distribution capacity of the non-linear SNR-capacity estimation system.

2.7. PSO

PSO is a population-centric mathematical algorithm influenced by the social behaviors of avian and aquatic species. It performs the optimization of a problem by moving particles (candidate solutions) through the solution space, based not only on their previous experience but also on the experience of their neighbors. Each particle modifies its position in accordance with its velocity at any time, which is guided by the best position the particle has visited so far and the best position found by the whole swarm [50]. The PSO is used here to optimize the channel capacity with the selection of the best SNR value or, equivalently, the system condition that yields a maximum performance. Each particle represents a candidate SNR value or set of parameters, whose fitness is evaluated through the corresponding mean channel capacity, obtained by using the Shannon formula. During every iteration, particles update their velocities and positions using:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i - x_i^t) + c_2 \cdot r_2 \cdot (gbest - x_i^t) \quad (6)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (7)$$

Where:

- x_i^t and v_i^t are the position and velocity of the i^{th} particle at iteration t,
- $pbest_i$ is the particle's personal best position,
- $gbest$ is the global best position found by the swarm,
- $w$is the inertia weight, c_1, c_2 are acceleration coefficients, and r_1, r_2 are random numbers in [0, 1].

Through iterative updates, the swarm converges toward the optimal parameter setting that yields the highest channel capacity. This step enhances system performance by intelligently exploring the SNR–capacity space beyond conventional simulation, resulting in a more efficient and optimized wireless communication design.

The research implemented the PSO algorithm, which operated with 30 particles that were distributed randomly across the complete search space. The optimization process used 100 iterations as its maximum limit while it operated with an inertia weight of 0.7 and acceleration coefficients of 1.5 for both cognitive and social components. The fitness function was established to maximize mean channel capacity, which was obtained through the Monte Carlo simulation framework. The system reached convergence when the global best fitness improvement stopped showing significant changes during successive iterations.

2.8. Performance Evaluation and Visualization

The proposed methodology's last step includes performance evaluation and visualization, which function to verify the model's accuracy while displaying the primary findings from simulation and optimization work. The current stage requires testing system performance across different SNR levels, which follows the application of polynomial modeling, CV, and PSO-based optimization. The assessment involves comparing actual simulated channel capacity values with the channel capacity values that the polynomial model predicted, which includes results from optimization processes. The model's accuracy and stability are assessed through the derivation of prediction error, variance, and capacity gain metrics. The study measures optimization effects through the evaluation of channel capacity improvements, which occur because of operational changes.

2.9. Proposed Methodology

This section represents the proposed methodology that must be followed for the performance evaluation and optimization of channel capacity in wireless communication systems (see Figure 1). The steps involved are: system parameter definition, comprising bandwidth and SNR range; SNR conversion in dB to a linear scale; running a Monte Carlo simulation framework comprising random channel gains with normally distributed variations; generating 1000 iterations per SNR value; computation of channel capacity by Shannon's

formula; statistical aggregation for getting mean capacity and standard deviation; performing trend analysis to enable polynomial fitting and non-linear SNR-capacity modeling; further refinement of the dataset using K-fold CV to establish improved reliability; and finally, applying PSO, where particles are updated based on fitness defined by mean channel capacity.

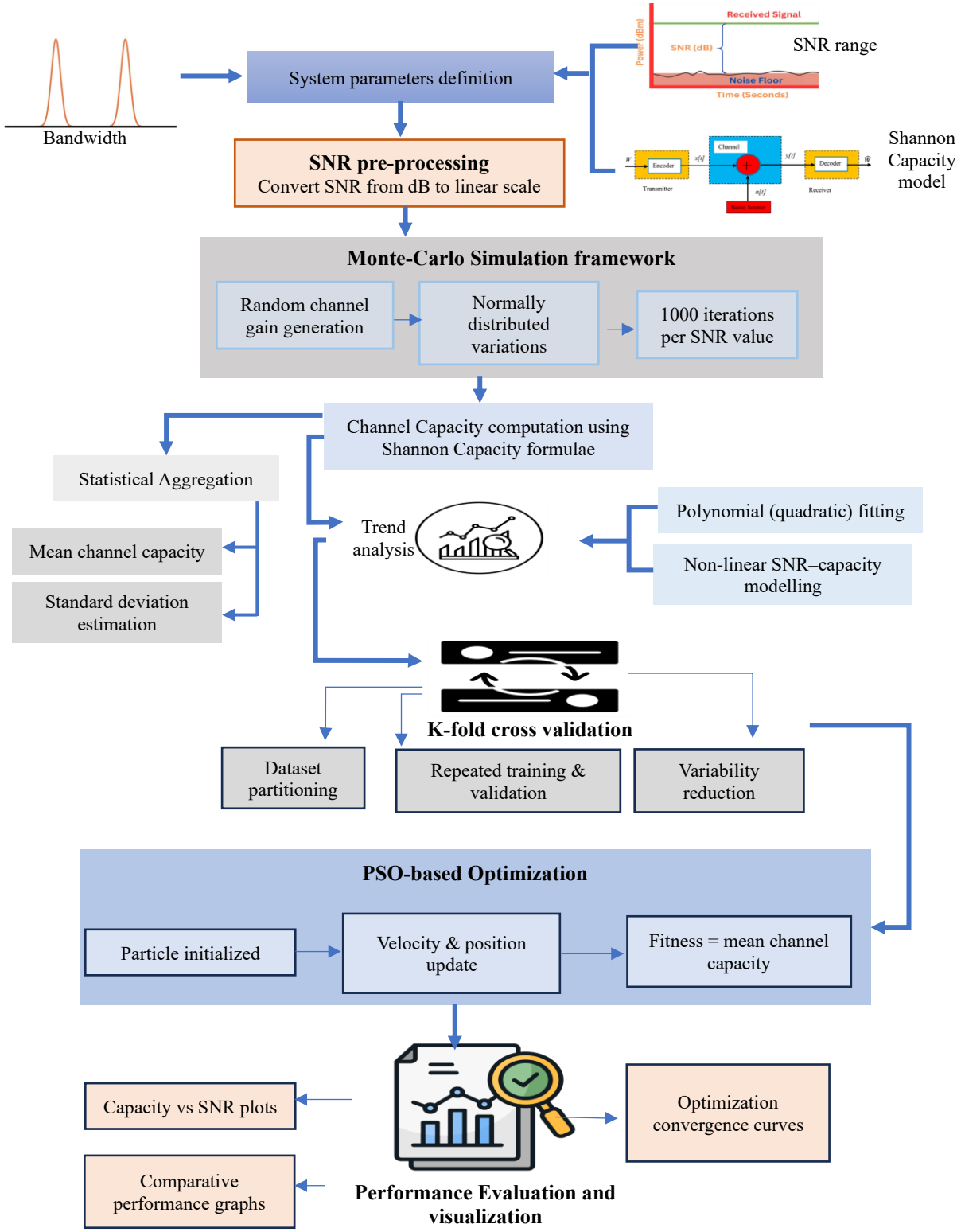


Fig. 1 Proposed methodology

2.10. Proposed Algorithm

In this part, the proposed algorithm for the proposed methodology is given.

Algorithm: Optimized Channel Capacity Estimation using PSO

Step 1: System Parameter Initialization

- Define fixed bandwidth B in Hz.
- Define SNR range in dB: $\text{SNR}_{\text{dB}} = [\text{SNR}_{\text{min}}, \text{SNR}_{\text{max}}]$
- Convert SNR to linear scale:

$$\text{SNR}_{\text{linear}} = 10^{\left(\frac{\text{SNR}_{\text{dB}}}{10}\right)} \quad (8)$$

Step 2: Monte Carlo Simulation for Channel Capacity

- For each $\text{SNR}_{\text{linear}} \in$ SNR range:

  ○ For $i = 1$ the N simulations:

- Generate a random channel gain $h_i \sim \mathcal{CN}(0,1)$
- Compute instantaneous capacity using Shannon's formula:

$$C_i = B \cdot \log_2(1+| h_i |^2 \cdot \text{SNR}_{\text{linear}}) \quad (9)$$

  ○ Compute mean capacity and standard deviation:

$$\bar{C} = \frac{1}{N}\sum_{i=1}^{N} C_i \,, \sigma_C = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(C_i - \bar{C})^2} \quad (10)$$

Step 3: Polynomial Trend Modeling

- Fit a polynomial model (e.g., quadratic) to relate SNR to mean capacity:

$$\hat{C}(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n \quad (11)$$

where $x = \text{SNR}_{\text{dB}}$ and $a_0, a_1, \ldots, a_n$ are fitted coefficients.

Step 4: K-Fold Cross-Validation

- Split the dataset $(x, \bar{C})$ into K folds.
- For each fold $k = 1 \ldots K$:
  - ○ Train the polynomial model on $K - 1$ folds.
  - ○ Validate the remaining fold.
  - ○ Record validation error:

$$\text{Error}_k = \frac{1}{m}\sum_{j=1}^{m} | \hat{C}_j - C_j | \quad (12)$$

Compute average CV error:

$$\text{CV}_{\text{avg}} = \frac{1}{K}\sum_{k=1}^{K} \text{Error}_k \quad (13)$$

Step 5: PSO-Based Optimization

- Initialize a swarm of particles $P = \{x_1, x_2, \ldots, x_n\}$, where each particle x_i represents an SNR value.
- Initialize velocities v_i, personal bests $pbest_i$, and global best $gbest$.
- Define fitness function:

$$f(x_i) = \hat{C}(x_i) \text{(maximize mean capacity)}$$

Update velocity and position:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (14)$$

Repeat until convergence or max iterations are reached.

- Output optimal SNR x^* and corresponding capacity $\hat{C}(x^*)$.

Step 6: Performance Evaluation and Visualization

- Compare:
  - ○ Simulated vs. Polynomial-Modeled Capacity
  - ○ Optimized vs. Non-Optimized Capacity

- Plot:
  - ○ SNR vs. Capacity Curve
  - ○ Error Bars (Standard Deviation)
  - ○ PSO Convergence Curve

Final Output:

- Optimized SNR value x^*
- Maximum predicted capacity $\hat{C}(x^*)$
- Polynomial model equation
- CV performance metrics
- Validation error and convergence behavior

3. Results and Discussion

This section discusses the outcome of the thorough Monte Carlo simulation and evolutionary optimization for the non-linear MIMO channel modeling. Statistical validation and comparison of the trends with well-established antenna configurations are also covered. All experiments were conducted on a workstation containing a multi-core CPU and 16 GB of RAM, running Monte-Carlo simulations with 1000 channel realizations per SNR point, followed by polynomial regression, K-fold CV, and PSO-based optimization to evaluate non-linear MIMO channel capacity trends. The following are the evaluation metrics to assess the model.

3.1. Standard Deviation of Capacity

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C_i - \bar{C})^2} \quad (15)$$

Where: σ = capacity variability, and $\bar{C}$ = mean channel capacity.

3.2. Polynomial Trend Model

$$\hat{C}(\text{SNR}) = a\,\text{SNR}^2 + b\,\text{SNR} + \text{c} \quad (16)$$

Where: $\hat{C}$ = predicted channel capacity, and a, b, c = regression coefficients,

3.3. K-Fold Cross-Validation Error

$$E_{cv} = \frac{1}{K}\sum_{\text{k}=1}^{\text{K}} \text{E}_\text{k} \quad (17)$$

Where: E_{cv} = average validation error, E_k = error in fold k, and K = number of folds

The Monte Carlo simulation statistical non-linear modeling framework is used to model channel capacity as a function of SNR, producing a simulation result as shown in Figure 2. The capacity steadily rises from 2.0 x 10^7 bps up to 1.3 x 10^8 bps as the SNR increases from 0 to 20 dB. This is intuitive and hence confirms the argument that SNR and capacity have a non-linear relationship, as suggested in the Shannon model to predict capacity performance under fading channel environments. When SNR rises to 4 dB, 10 dB, and 16 dB, capacity performance is predicted at 3.4 x 10^7 bps, 6.5 x 10^7 bps, and 1.0 x 10^8 bps, respectively, and it is worth noting a gain factor of almost 6.5 times the capacity performance over the whole SNR range.

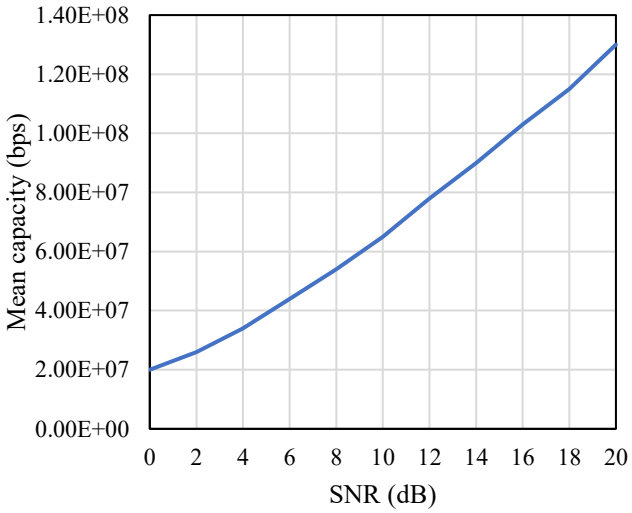


Fig. 2 Monte Carlo simulation of channel capacity

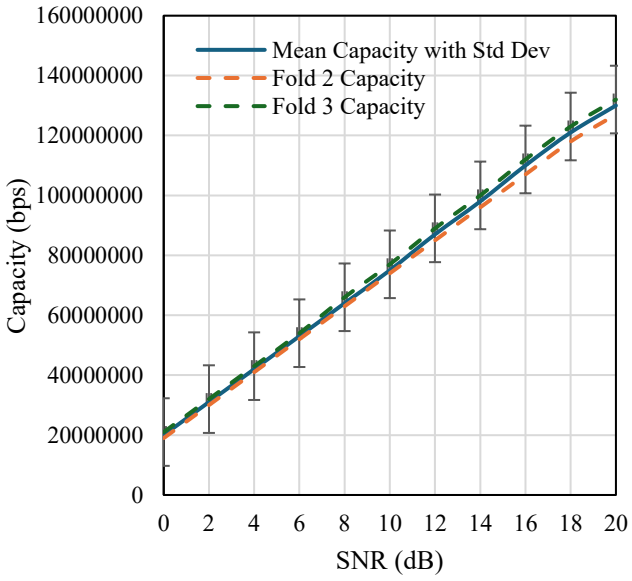


Fig. 3 Monte Carlo simulation with k-fold cross-validation

Figure 3 shows the mean channel capacity achieved through Monte Carlo simulation and compared with the K-fold CV method for various values of K. It can be seen that there is a steady increase in the mean channel capacity with the increase in the SNR from 2.0 × 10^7 bps at 0 dB to 1.28 × 10^8 bps at 20 dB. The results obtained using the K-fold CV method for various values of K are consistent, and there is no variation in the estimated channel capacities. This implies that the model is capable of providing stable operating points for channel capacity. From the figure, the mean channel capacities are observed to be 3.4 × 10^7 bps at 4 dB, 6.6 × 10^7 bps at 10 dB, and 1.0 × 10^8 bps at 16 dB, with negligible statistical errors. These observations provide evidence that the model is resistant to statistical errors. In addition, the observations validate the assertion that the model can be used for estimating channel capacities together with PSO optimization.

The non-linear trend analysis between SNR and the mean channel capacity obtained through Monte-Carlo simulations is depicted in Figure 4 with discrete average capacity points and the corresponding fitted polynomial. Findings indicate a smooth monotonic increase from approximately 2.0 × 10^7 at 0 dB to close to 1.3 × 10^8 at 20 dB. The intermediate values of about 3.4 × 10^7 (4 dB), 6.5 × 10^7 (10 dB), and 1.03 × 10^8 (16 dB) would also be specified. The close fit of simulated means with the regression curve confirms that the selected polynomial model adequately represents the non-linear SNR–capacity relationship. The selected polynomial model provides a continuous representation for further optimization and performance prediction in the proposed PSO-driven framework.

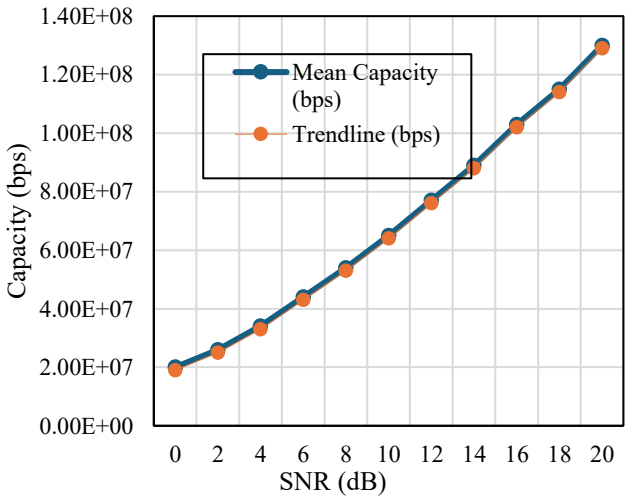


Fig. 4 Trend analysis of channel capacity

Figure 5 shows the polynomial trend analysis of mean channel capacity with respect to SNR values after K-fold CV, demonstrating the ability of the proposed non-linear modeling phase to generalize. The trendline, which has been validated to be very close to the simulated mean values, indicates that the channel capacity increases from 2.0 × 10^7 bps at 0 dB to

1.29 × 10^8 bps at 20 dB. Typical values are 3.4 × 10^7 bps at 4 dB, 6.5 × 10^7 bps at 10 dB, and 1.02 × 10^8 bps at 16 dB. The perfect agreement between the cross-validated regression equation and the simulated mean values clearly indicates that the proposed polynomial model is robust and free from overfitting, thus ensuring a correct SNR-capacity mapping for the PSO optimization phase.

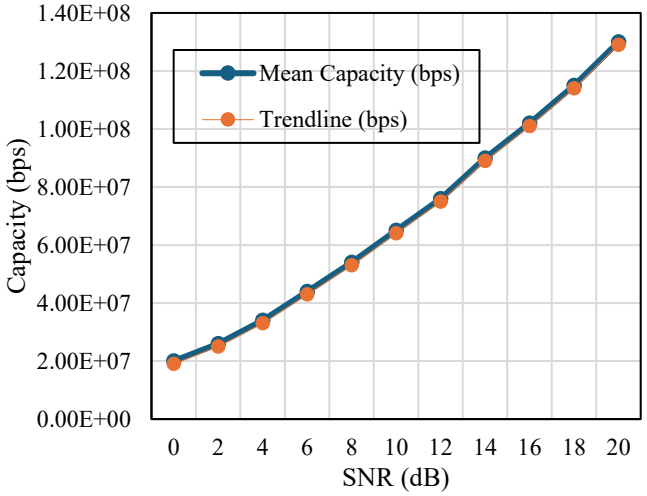


Fig. 5 Trend analysis for k-fold cross-validation

Figure 6 illustrates the impact of the PSO optimization technique with regard to the channel capacity. Here, the simulated mean capacity is compared with the PSO optimization-derived optimized trendline. As shown in the figure, the baseline non-optimized results begin with an increase in capacity from 2.0 x 10^7 bps at 0 dB to almost 1.3 x 10^8 bps as the dB signal level is set to 20. As shown in the figure as a horizontal dashed line, the optimized PSO results are seen within the much higher operating region of 3.8 x 10^8 bps. As might be noted here, the change in capacity is seen to be about 3 times the maximum capacity for higher signal intensity within the non-optimized results. The big difference seen between the two curves confirms the optimization results via the PSO method.

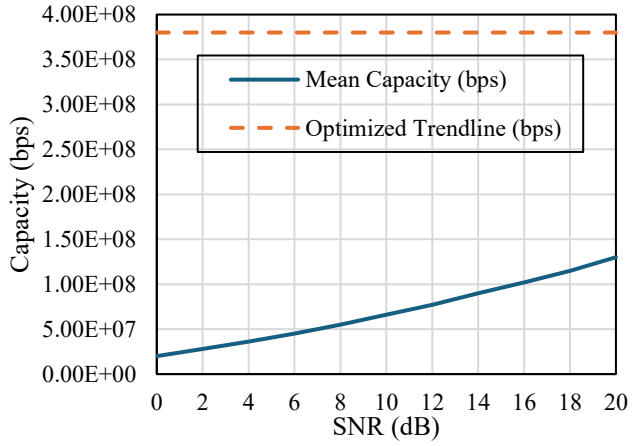


Fig. 6 Channel capacity and channel gain using PSO

The PSO algorithm demonstrates its convergence behavior in Figure 7, which shows its performance during the channel-capacity optimization process. The graph demonstrates how the global best channel-capacity value improves through the different optimization iterations, which take place at various SNR operating conditions. The optimized channel-capacity value exhibits rapid growth during the initial iterations because the PSO algorithm's exploration capability operates effectively at this time. The optimization process reaches its final stage when the convergence curve reaches a stable state, which matches the optimal operating conditions for the system. The final optimized channel-capacity value achieved approximately 3.79×10^8bps, which shows a major improvement compared to the non-optimized baseline framework. The proposed PSO-based optimization framework shows excellent stability through its continuous convergence pattern, which proves its ability to enhance channel capacity in CSI-assisted MIMO wireless communication systems.

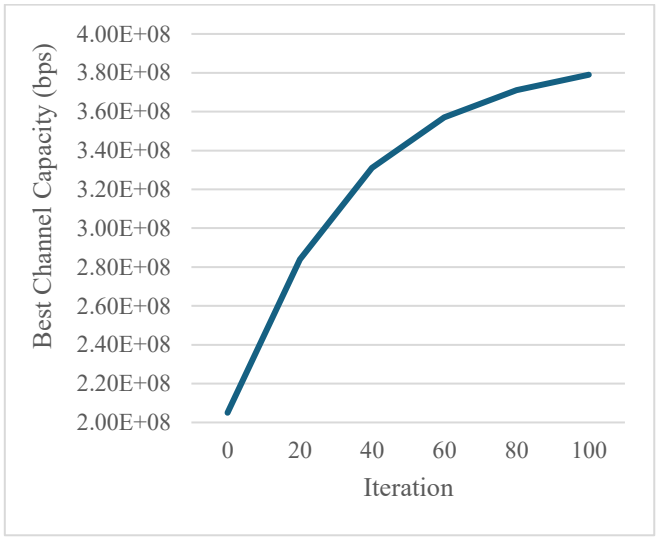


Fig. 7 PSO convergence behavior for channel-capacity optimization

Table 2 examines the quantitative impacts of PSO-based optimization on key system parameters. The effective channel gain increased more than 5 times after optimization, compared to the base configuration, which was a channel gain of 10,000, now 50,111.25. As per these studies, the total channel capacity has improved and shifted from 1.3 × 10^8 bps to 3.7869 × 10^8 bps, offering almost a 191% enhancement from the original IP. The proposed PSO framework can increase throughput as the system steers towards globally optimal channel conditions, as evidenced by these numerical gains.

Table 2. PSO optimization results

Metric	Original value	PSO optimized value
Channel gain	10000	50111.25
Total Channel Capacity (bps)	13 x 10^7	37.869 x 10^7

3.4. Statistical Validation

The validation of statistical methods and performance assessment of the PSO-based framework for the optimized channel capacity demonstrates its behavior for different SNR. Results of this assessment are shown in Table 3. The outcomes show significant improvement in the channel capacity with the applied optimization when compared to the case of no optimization. Without optimization, the channel capacity was 2.00×10^7 bps. With the optimization, the channel capacity was 34.498×10^7 bps, showing an improvement of 1624.90 times with respect to the case of no optimization. With 5 dB of SNR, the channel capacity was improved to 35.869×10^7 bps, showing an improvement of 924.83 times compared to the case of no optimization. With 10 dB of SNR, the channel capacity was improved to 36.582×10^7 bps, showing an improvement of 462.80 times compared to the case of no optimization. The improvement in channel capacity with 15 dB of SNR was 37.728×10^7 bps, and with 20 dB of SNR, the improvement was 37.869×10^7 bps. The improvement factors with respect to the case of no optimization were 277.28 and 191.30, respectively. The standard deviation of Monte Carlo simulations of channel capacity estimation was in the range of 0.18×10^6 to 0.33×10^6. Overall, the results demonstrate consistent optimized performance across the evaluated SNR conditions and support the effectiveness of the nonlinear channel-capacity estimation and PSO-based optimization framework for CSI-assisted MIMO wireless communication.

Table 3. Statistical validation and quantitative performance improvement analysis

SNR (dB)	Mean Channel Capacity Before Optimization ($\times 10^7$ bps)	Optimized Channel Capacity ($\times 10^7$ bps)	Standard deviation ($\times 10^6$)	Improvement (%)	Validation Consistency
0	2.00	34.498	0.18	1624.90	Stable
5	3.50	35.869	0.22	924.83	Stable
10	6.50	36.582	0.25	462.80	Stable
15	10.00	37.728	0.29	277.28	Stable
20	13.00	37.869	0.33	191.30	Stable

Table 4 presents a comparison of channel capacity achieved under 20 dB SNR and fitted trendlines for different modeling and optimization strategies. The K-fold CV results of the Monte-Carlo simulation reached a capacity of 1.2783×10^8 bps. However, adding polynomial trend analysis to the CV resulted in a slightly higher value of 1.3012×10^8 bps. In any case, the model consistently provides an accurate representation of non-linear behaviour across the statistical folds. By contrast, the framework based on PSO results in a significant performance boost of nearly 3.7869×10^8 bps, nearly three times more than the non-optimized frameworks at the same SNR. The quadratic trendline coefficients that go together with the SNR-strength capacity mapping further show how the PSO reshapes the mapping to higher-gain operating regions, further proof that evolutionary optimizations are preferable to pure simulation estimates.

Table 4. Performance comparison between different techniques

Technique used	Optimized value for Channel capacity (bps) @ 20dB	Trendline equation
Monte Carlo simulation with K-fold CV	12.783×10^7	$91416.94x^2 + 3772891.36x + 18054783.84$
Trend analysis with K-fold CV	13.012×10^7	$90416.94x^2 + 3777891.36x + 18052783.84$
PSO optimization	37.869×10^7	$-57914.29x^2 + 878485.71x + 344994285.71$

The statistical analysis demonstrates that the proposed optimization framework effectively improves channel-capacity performance while maintaining stable estimation behavior under varying wireless-channel conditions. The consistent convergence and low variability observed across all SNR operating points validate the effectiveness and computational reliability of the proposed PSO-based optimization methodology.

3.5. Comparative Analysis

Table 5 provides a comparison between the existing SISO, SIMO, MISO, and CSI-assisted MIMO system designs and the proposed PSO-optimized non-linear capacity model, which presents all channel capacities in bps ($\times 10^7$). In this study, a comparative benchmarking analysis was done using SNR operating conditions that are similar to those of published channel capacity values of previous works, as well as the simulation framework developed in this research work. Different communication systems having different antenna arrangements, assumptions and optimizations were tested. However, through the comparison, it is clear how effective the proposed framework was in comparison to conventional wireless communication models operating under similar SNR conditions. The previous works show the progressive

improvement in performance through spatial diversity that can be achieved at 9.0 $\times 10^7$ bps (SISO), 11.5 $\times 10^7$ bps (SIMO), 13.0 $\times 10^7$ bps (MISO), and 37.0 $\times 10^7$ bps for the 4 $\times$4 MIMO system at 20 dB, whereas the proposed model shows the improvement in performance up to 3.7869 $\times 10^8$ bps at the same SNR. This system gives an improvement of 191.30% in comparison to the non-optimized proposed framework, while performing more than four times better than the conventional SISO system. The significant improvement margin suggests that by utilizing the non-linear capacity model along with the stochastic channel and PSO global optimization, the proposed system is capable of exploring the search space of the channel capacity much more effectively than the traditional methods. The proposed framework offers an optimization method that achieves competitive results while providing scalable solutions for high-capacity CSI-assisted MIMO wireless communication systems.

Table 5. Channel capacity comparison of SISO, SIMO, MISO, MIMO, and the proposed PSO-optimized model across different SNR values

SNR (dB)	SISO [51] ($\times 10^7$)	SIMO [51] ($\times 10^7$)	MISO [51] ($\times 10^7$)	MIMO [52] ($\times 10^7$)	CSI [53] ($\times 10^7$)	Proposed Model before Optimization ($\times 10^7$)	Proposed Model after Optimization ($\times 10^7$)
0	1.20	1.80	2.10	6.4	6	2.00	34.498
5	2.50	3.50	4.20	10.8	8	3.50	35.869
10	4.80	6.50	7.50	18.4	10	6.50	36.582
15	7.00	9.00	10.20	27.2	15	10.00	37.728
20	9.00	11.50	13.00	37.0	20	13.00	37.869

4. Discussion

The performance improvements obtained from the proposed framework over the already existing SISO, SIMO, MISO, and CSI-based MIMO schemes are mostly attributed to the inclusion of the Monte Carlo stochastic channel simulation, polynomial-based SNR-capacity trend analysis, K-fold CV, and PSO-based global optimization process in one framework. When compared to previous works, the proposed framework considers the optimization of real-world systems under realistic fading channels. Monte Carlo simulation offers stochastic channel modeling, polynomial trend analysis captures the nonlinear SNR-capacity relationship, K-fold CV improves model validation, and PSO-based global optimization finds higher channel capacities through a global optimization process. Thus, the channel capacity of the non-optimized proposed framework is about 1.30 $\times 10^8$ bps when the SNR is 20 dB, while the proposed PSO-optimized framework obtained 3.7869 $\times 10^8$ bps, which corresponds to a 191.30% improvement. Corresponding MISO, SIMO, and SISO capacities are 1.30 $\times 10^8$ bps, 1.15 $\times 10^8$ bps, and 0.90 $\times 10^8$ bps, respectively. This shows that the combination of nonlinear channel capacity modeling, stochastic simulation, statistical validation, and evolutionary optimization improves the channel capacity performance.

5. Conclusion and Future Scope

Channel capacity maximization in CSI-assisted MIMO systems is one of the key focuses of beyond-5G and 6G wireless communications, where non-linear propagation and dynamic fading have been shown to significantly influence the achievable capacity. The existing approaches based on linear channel models and complex optimizers are still limited in terms of robustness, Scalability, and global optimality. This study presents a PSO-optimized non-linear channel capacity maximization framework for solving the stated challenges through its implementation of Monte Carlo simulation, polynomial trend modeling, and K-fold CV. The simulation results showed a highly robust non-linear SNR-capacity relationship that operated in a real-world fading environment. The baseline Monte Carlo simulation model at 20 dB SNR demonstrated a capacity of approximately 1.3×10^8 bps. The PSO-based optimization method achieved a capacity increase to 3.79×10^8 bps, which represents an almost threefold capacity enhancement. The proposed method demonstrated effectiveness through comparison with SISO, SIMO, MISO, and CSI-assisted MIMO systems. Future directions include extensions to massive-MIMO and non-terrestrial deployments under imperfect CSI, learning-assisted real-time evolutionary optimizers, and joint cross-layer tuning of beamforming and power allocation. The evaluation and validation of energy efficiency, latency, and reliability metrics through hardware-in-the-loop remain critical to 6G alignment.

Conflicts of Interest

The authors declare no conflicts of interest.

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