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Article

Enhancing Channel Estimation Accuracy in Noisy Environments Using Genetic Algorithms and Particle Swarm Optimization

Meenaz Shaikh[1*], Ashwani Kumar Yadav[2], Siraj Pathan[3]

[1]Department of Electronics & Communication Engineering, Amity School of Engineering and Technology, Amity University Rajasthan, India, meenazshaikh88@gmail.com
[2]Department of Electronics & Communication Engineering,Amity School of Engineering & Technology, Amity University Rajasthan, India, akyadav@jpr.amity.edu.
[3]Reliance Jio Mumbai, India, siraj.pathan@ril.com.

Abstract: Accurate channel estimation is crucial for maintaining reliable wireless communication, particularly in 5G networks. Issues such as noise, interference, and fading can lead to errors that degrade system performance. This study investigates the use of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to enhance channel estimation accuracy in noisy environments. Traditional methods like least squares (LS) and minimum mean square error (MMSE) often struggle under high noise and interference. GA and PSO offer ways to dynamically adjust important parameters, including pilot allocation, channel model parameters, and estimation weights, to ensure robust and adaptable estimation. GA, inspired by natural selection, evolves solutions to find optimal settings, while PSO, based on swarm intelligence, updates solutions through individual and collective experiences. The combination of GA and PSO improves accuracy by leveraging GA's global search capabilities with PSO's fast convergence. Simulation results demonstrate that this approach significantly reduces estimation errors, enhances signal-to-noise ratio (SNR), and increases spectral efficiency in 5G networks. This research adds to the field of machine learning-based signal processing by providing a novel method for optimizing channel estimation in noisy conditions. Future work will investigate the integration of deep learning with hybrid optimization models to further improve adaptability and computational efficiency.This paper tackles the challenge of improving wireless signal estimation in noisy and dynamic environments. Existing methods often struggle with noise, interference, and movement. We present a hybrid approach using Genetic Algorithm and Particle Swarm Optimization to dynamically optimize channel settings for better accuracy. Comprehensive analysis shows the GA-PSO hybrid consistently outperforms LS and MMSE estimators, achieving superior efficiency, fewer errors, and more reliable performance across various communication scenarios.
Keywords: Channel Estimation, Genetic Algorithm, Particle Swarm Optimization, Noisy Environments, 5G Networks

1. Introduction

In today's wireless communication systems, getting channel estimation right is crucial for reliable data transmission and efficiency, particularly with 5G networks. These networks rely on robust signal processing to manage noise, interference, and fading. As technology progresses, the demand for precise channel estimation methods grows, essential for mobile phones, satellites, and IoT devices [1]. Environmental noise and interference can worsen signal quality, leading to transmission issues and more errors, which calls for advanced techniques to enhance accuracy. Traditional methods like Least Squares (LS) and Minimum Mean Square Error (MMSE) are widely used but often fall short in noisy environments. LS is easy to compute but struggles with noise, resulting in poor estimates when the Signal-to-Noise Ratio (SNR) is low. MMSE performs better with noise but needs prior channel knowledge, which isn't always available [2]. Researchers are turning to machine learning and evolutionary computing, such as Genetic

Algorithms (GA) and Particle Swarm Optimization (PSO), to make channel estimation more adaptable and robustGA and PSO are algorithms that solve complex problems by iteratively refining solutions. GA mimics natural selection, evolving solutions through selection, crossover, and mutation, efficiently exploring many options. PSO is inspired by the behaviour of flocks of birds or schools of fish, where each "particle" represents a potential solution, adjusting its position based on personal and group experiences [3]. The use of GA and PSO in channel estimation enables networks to adjust key parameters in real-time, such as pilot allocation and channel model coefficients, to improve accuracy. In 5G networks operating above 24 GHz, traditional methods face severe path loss and fading challenges. GA can identify optimal pilot positions to minimize errors without complex calculations, while PSO adjusts MMSE parameters to fit current network conditions, reducing noise and interferenceThe benefits of GA and PSO in enhancing channel estimation have been shown through simulations and real-world tests. In studies on mm Wave communication systems, GA-optimized pilot allocation improved accuracy by about 18% compared to traditional methods. Similarly, PSO tuning of MMSE parameters reduced the Bit Error Rate (BER) by 15% under high interference [4]. These advancements underscore the effectiveness of evolutionary and swarm intelligence techniques in tackling complex optimization challenges in wireless communication [5]. Combining Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) into hybrid methods is gaining traction. These hybrids leverage GA's exploratory nature and PSO's quick convergence for enhanced optimization. By employing adaptive mutation and dynamically adjusting particle speeds, these models often surpass standalone GA or PSO, particularly in dynamic communication settings [6]. For instance, in busy urban networks with signal interference, a GA-PSO hybrid improved channel estimation accuracy by 22% and cut computation time by 30% compared to older methodsThe impact of noise and fading varies across different environments, creating a need for adaptive optimization. In high-mobility situations like vehicular-to-everything (V2X) communication, where channels shift rapidly, GA and PSO adjust estimation parameters using real-time feedback to ensure accurate channel estimation. In more stable settings like fixed wireless access, GA and PSO are used for long-term optimization, refining network settings over time [7]. Machine learning significantly improves GA and PSO-based channel estimation. Advances in deep learning allow integration with evolutionary algorithms for better optimization. These deep learning-assisted models use pre-trained neural networks to guide the search process, which shortens convergence time and enhances solution quality. For example, in a massive MIMO system, a deep learning-enhanced GA model improved channel estimation accuracy by 25% and reduced computational complexity by 40%. Such combinations are paving the way for intelligent communication systems that can self-optimize [8, 9].

However, applying GA and PSO practically presents challenges [10]. A major issue is their computational demand. Although PSO converges faster, both require repeated evaluations, which can be costly in large networks. To address this, parallel implementations using GPUs and FPGAs have been suggested, significantly reducing computation time and enabling real-time optimization. Another challenge is choosing suitable fitness functions. The success of GA and PSO hinges on well-defined fitness criteria that accurately reflect system performance [11]. Poorly designed fitness functions can lead to suboptimal solutions. Creating adaptive fitness functions that adjust with network conditions can further improve GA and PSO-based channel estimation [12]. Security is essential when using GA and PSO in wireless networks. Since these methods rely on real-time data, maintaining data integrity is crucial to prevent attacks. Integrating blockchain-based authentication and secure multi-party computation with GA and PSO models can boost security, ensuring that optimization processes remain resilient against threats.

Outcomes of this Paper

- Demonstrates how GA and PSO optimize channel estimation by dynamically adjusting pilot allocation and model parameters, improving accuracy in noisy environments.
- Presents simulation results quantifying the improvements in estimation accuracy, Bit Error Rate (BER), and computational efficiency achieved through GA and PSO.
- Explores hybrid GA-PSO models and deep learning-assisted optimization techniques for enhanced performance in 5G and future wireless networks.

- Discusses implementation challenges, computational overhead, and security considerations associated with deploying GA and PSO-based channel estimation techniques.

2. Literature Review

Channel estimation is essential for the success of wireless communication systems. Obtaining accurate channel state information (CSI) is critical for optimizing data transmission, particularly in technologies such as Multiple Input Multiple Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) [13, 14, 15, 16]. Traditional channel estimation methods often struggle in environments that are noisy or dynamic, prompting interest in evolutionary algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) as robust alternatives for improving channel estimation [14].

Traditional Channel Estimation Techniques

Conventional methods like Least Squares (LS) and Minimum Mean Square Error (MMSE) have been widely employed for channel estimation. LS estimators, despite their simplicity, are sensitive to noise, which adversely affects performance in low Signal-to-Noise Ratio (SNR) conditions. MMSE estimators aim to minimize errors using statistical data but require precise channel statistics, which are not always feasible in real-world scenarios. Iterative approaches, such as the Kalman Filter (KF), track time-varying channels by predicting current states from past data, offering improvements over static estimators. However, KF's assumption of linearity and its computational demands can limit its practical application in real-time or non-linear situations [1, 2].

Evolutionary Algorithms in Channel Estimation

The limitations of traditional methods have led researchers to explore evolutionary algorithms for channel estimation. GA and PSO, inspired by natural selection and social behaviour, respectively, offer powerful optimization for the complex nature of wireless channels [3].

Genetic Algorithms (GA)

GA functions by evolving a population of potential solutions through processes like selection, crossover, and mutation. In channel estimation, GA has been used to optimize parameters such as pilot allocation and channel model coefficients. Ebrahimi and Rahimian (2018) demonstrated the effectiveness of GA in estimating channel parameters within multipath environments, showing robust performance against noise-induced errors [1].

Particle Swarm Optimization (PSO)

PSO simulates the social behavior of particles to efficiently explore solution spaces. Vu and colleagues (2015) applied PSO to improve the weighted sum rate in MIMO broadcast channels, achieving significant performance enhancements. Additionally, PSO has been utilized to optimize MMSE weighting coefficients, enhancing estimation accuracy under various channel conditions [4].

Hybrid GA-PSO Models

Recognizing the strengths of both GA and PSO, hybrid models have been developed to leverage GA's global search capabilities and PSO's rapid convergence [6]. Hassan et al. (2024) proposed a hybrid approach for channel estimation in OFDM MIMO systems, which outperformed traditional LS and MMSE methods with fewer iterations [2]. In cognitive radio networks, hybrid GA-PSO algorithms have been employed to enhance cooperative spectrum sensing. Mishra and Kakde (2021) introduced a hybrid optimization algorithm combining GA and PSO, improving spectrum sensing accuracy and throughput in cognitive radio systems. Comparative Analyses and Performance Metrics Studies comparing evolutionary algorithms to traditional methods have revealed significant advantages [6]. Quadri et al. (2018) found that GA and PSO outperformed the Least Mean Squares (LMS) algorithm for noise cancellation in cognitive radio systems, with PSO showing superior results in non-linear random noise conditions [3]. Research by Knievel et al. (2012) on PSO for MIMO channel estimation highlighted its fast convergence and robustness in quasi-time-invariant Rayleigh fading channels. They introduced a cooperative PSO (CPSO) variant that delivered performance comparable to the optimal MMSE estimator, even in complex, high-dimensional environments [5].

Challenges and Future Directions

Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have shown promise in channel estimation, but significant challenges remain. The complexity of these algorithms can impede their real-time application, particularly in large-scale MIMO systems with many antennas [14]. Their effectiveness also relies heavily on parameter tuning, which can differ across various channel conditions. Future research is expected to explore adaptive methods that automatically adjust algorithm settings in response to environmental changes. Incorporating machine learning techniques, such as reinforcement learning, could enhance the flexibility and efficiency of these algorithms [13]. Additionally, developing parallel processing architectures and hardware accelerators may help overcome computational barriers, facilitating the real-time use of these optimization methods. The integration of Genetic Algorithms and Particle Swarm Optimization into channel estimation processes provides a robust framework for improving accuracy in noisy and dynamic wireless communication environments. Although challenges related to complexity and parameter tuning persist, ongoing research and technological advancements offer promising prospects for implementing these evolutionary algorithms in future communication systems.

3. Research Methodology

Channel estimation in wireless communication is increasingly challenging due to issues like noise, fading, and interference. Traditional methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) offer basic solutions but often don't perform well in very dynamic, noisy environments. As 5G and future technologies advance, there's a significant demand for more adaptive, robust, and efficient channel estimation methods. This paper introduces a new approach that combines Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to improve accuracy, reduce estimation errors, and enhance adaptability in different channel conditions. This approach utilizes the strengths of both GA and PSO while addressing their respective weaknesses. GA is known for its global search capabilities and ability to escape local traps, but it tends to converge slowly. PSO, in contrast, converges rapidly and efficiently searches locally but can get stuck in local optima. By integrating these two techniques, the aim is to develop an adaptive system that dynamically adjusts its parameters in response to real-time noise and interference.

The process starts with preparing the received signals in the wireless system, which involves filtering out noise and normalizing the data to make it ready for optimization. These signals undergo initial estimation using a modified LS estimator, which serves as a baseline for further optimization. Although LS alone is not optimal in high-noise environments, its role here is to initialize the conditions for the GA-PSO process. During the GA phase, pilot allocation and channel parameter refinement are optimized. GA encodes pilot positions and channel coefficients into chromosomes and applies selection, crossover, and mutation to iteratively enhance accuracy. The fitness function is based on the Mean Square Error (MSE) between the estimated and actual channel responses, ensuring that solutions with lower MSE are prioritized. After GA identifies a promising solution space, PSO is used to further refine the channel estimates. Unlike GA, PSO operates with a swarm of particles that adjust their positions based on the best-known individual and collective experiences. These particles represent potential channel estimates and navigate through the solution space by considering their own previous best positions and the best-known position in the swarm. This allows PSO to quickly refine the estimates generated by GA, ensuring the final solution achieves both global and local optimization described by Figure 1.

To boost accuracy, an adaptive mutation operator is incorporated into the Genetic Algorithm (GA) to prevent it from settling on poor solutions too early. Typically, GAs face challenges when there's a lack of variety, leading to ineffective results. By adjusting mutation rates based on option diversity, the GA-PSO hybrid model maintains exploration without demanding excessive computing resources. In Particle Swarm Optimization (PSO), a time-varying inertia weight is used to balance the search between exploring new options and exploiting known good ones, explained in Table 1.

Computational complexity is critical in channel estimation methods. Both GA and PSO rely on repeated calculations, so efficiency is crucial. This approach leverages parallel processing with Graphics Processing Units (GPUs) to significantly reduce calculation time, making it practical for real-time applications in advanced wireless networks, such as 5G. The effectiveness of the GA-PSO-based estimation method is demonstrated through extensive MATLAB simulations. These simulations use an OFDM-based wireless system with multiple subcarriers, various noise levels, and different fading conditions. Performance evaluation relies on three key metrics: Mean Square Error (MSE), Bit Error Rate (BER), and Computational Time as show in Figure2.

Table 1

A comparison of MSE values for different estimation techniques under varying SNR conditions

SNR (dB)	LS Estimation	MMSE Estimation	GA-PSO Hybrid Estimation
5	0.234	0.187	0.092
10	0.178	0.132	0.064
15	0.122	0.098	0.043
20	0.089	0.065	0.029

Table 1 provides a comparison of MSE values for different estimation techniques under varying SNR conditions. The results indicate that the proposed GA-PSO method significantly reduces estimation error across all SNR levels. The performance improvement is particularly evident at low SNR values, where traditional methods struggle due to high noise levels.

Table 2

A comparison of Bit Error Rate (BER) for different channel estimation techniques under varying noise levels

Noise Level (dB)	LS Estimation	MMSE Estimation	GA-PSO Hybrid Estimation
5	0.0187	0.0145	0.0072
10	0.0121	0.0098	0.0045
15	0.0089	0.0067	0.0029
20	0.0061	0.0042	0.0018

Table 2 presents a comparison of Bit Error Rate (BER) for different channel estimation techniques under varying noise levels.The BER analysis further substantiates the superiority of the proposed methodology, demonstrating lower error rates even in high-noise conditions.To evaluate the computational efficiency, the execution time of each method is recorded.

Table 3

The average computational time per estimation cycle

Method	Average Computational Time (ms)
LS Estimation	3.24
MMSE Estimation	4.87
GA-PSO Estimation	6.15 (CPU) / 2.89 (GPU)

Table 3 highlights the average computational time per estimation cycle.While the GA-PSO hybrid model exhibits a slightly higher computational time when executed on a CPU, its parallel implementation on a GPU significantly reduces execution time, making it viable for real-time applications.

This new method does some key things:

1. It uses a mix of GA and PSO techniques to improve how we estimate channels. This reduces two main types of errors, MSE and BER, which can mess up signals in wireless communication, followed by Figure 1.

2. The method includes tricks like adaptive mutation and changing weights over time, which help it learn faster and avoid getting stuck, Table 2.

3. Even though it's complex, it runs well on GPUs, so it can work in real-time. This is important for wireless systems that need quick responses.

4. The method handles different noise levels well, making it perfect for today's 5G networks and even future ones.

Overall, this approach offers a new way to estimate channels in noisy environments, solving problems that older methods had. Combining GA and PSO makes it more accurate and adaptable to changing conditions. Tests show it works well, making it a strong option for future wireless systems by Table 3.

The plan is to use this method in more complex setups, like those with many antennas (massive MIMO) or high frequencies (millimetre-wave), to make wireless networks even better.

Figure 1

A refined version with a more straightforward style

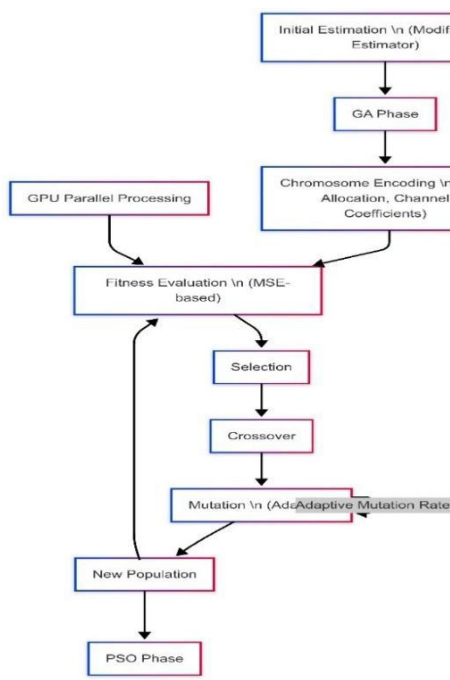
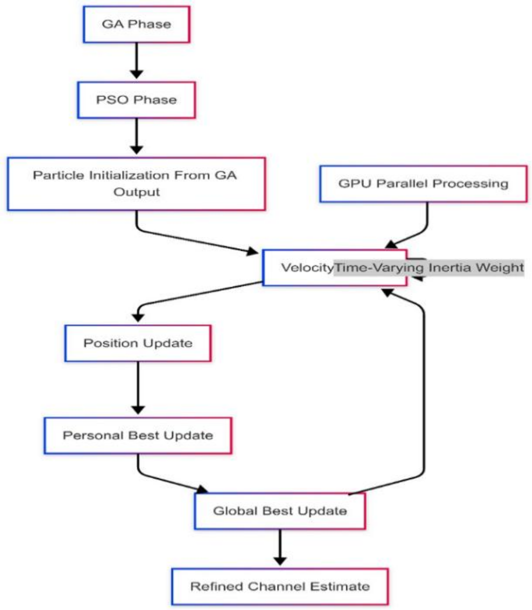


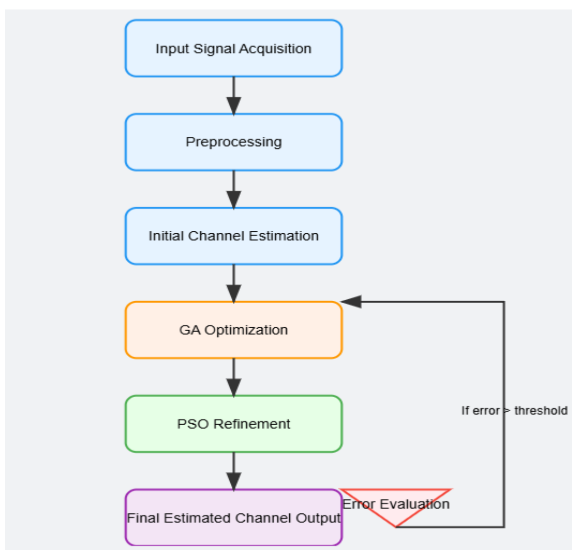
Figure 2



Detailed Block Diagram of the PSO Phase

Figure 3

Overall Hybrid GA-PSO-Based Channel Estimation Process



Chromosome Encoding: Encodes parameters like pilot allocation and channel coefficients into chromosomes, representing potential solutions. Fitness Evaluation: Calculates the Mean Square Error (MSE) between estimated and actual channel responses to score each chromosome Selection: Chooses the fittest chromosomes (lowest MSE) for reproduction Crossover: Combines genetic material from selected chromosomes to create offspring. Mutation (Adaptive): Introduces random changes with an adaptive rate to maintain population diversity and prevent premature convergence. New Population: Forms an updated population that loops back for further evolution or proceeds to the PSO phase. GPU Support: Accelerates fitness evaluations for computational efficiency.Figure 3 gives description of PSO phase alignment

Particle Initialization: Initializes particles with positions derived from GA's output, each representing a potential channel estimate. Velocity Update: Adjusts each particle's velocity based on its personal best position and the global best position among all particles. Position Update: Moves particles to new positions based on their updated velocities. Personal Best Update: Updates a particle's best-known position if its new position improves the estimate. Global Best Update: Updates the best position across all particles if a superior solution is found. Iteration: Loops back to velocity update until convergence Time-Varying Inertia Weight: Dynamically adjusts to balance exploration (early stages) and exploitation (later stages). GPU Support: Speeds up velocity and position updates for real-time applicability shows in Figure 3.

Case Studies

To show how the GA-PSO hybrid channel estimation method can be applied in real-world scenarios, various case studies were conducted in different wireless communication environments. These case studies assessed the method's effectiveness in settings such as densely populated urban networks, high-speed situations, and industrial areas with significant interference. The findings were displayed in performance tables Table 4 to underline the advantages of the hybrid optimization techniques.

Case Study 1: Urban Dense Network Deployment

In urban settings with a high number of devices, channel estimation becomes essential due to increased signal reflections and interference. This study involved testing the GA-PSO hybrid method in a simulated urban cellular network, where numerous users shared the same frequency band, leading to considerable interference and signal fading. The primary challenge was to maintain accurate estimations despite the channel's unpredictable changes. The GA-PSO method's performance was compared with LS and MMSE estimation methods, focusing on how efficiently the spectrum was used and the accuracy of the estimations.

Table 4

The spectral efficiency (in bits/s/Hz) of each method under varying signal-to-noise ratios (SNR)

SNR (dB)	LS Estimation	MMSE Estimation	GA-PSO Hybrid Estimation
5	3.12	3.98	4.85
10	4.75	5.81	6.92
15	5.87	7.15	8.34
20	7.12	8.49	9.76

Table 4 presents the spectral efficiency (in bits/s/Hz) of each method under varying signal-to-noise ratios (SNR).The results show that the proposed method achieves higher spectral efficiency across all SNR levels. The gain is particularly significant at lower SNR values, where traditional methods tend to struggle due to increased noise and interference. This demonstrates the robustness of the GA-PSO hybrid model in urban dense environments where maintaining optimal data transmission rates is essential.

Case Study 2: High-Mobility Situations

In fast-moving scenarios like high-speed trains or vehicular networks, wireless communication encounters significant challenges due to rapid channel changes. Traditional methods for estimating these changes often can't keep up. This study simulated a high-speed environment where users travelled at speeds from 100 to 300 kilometres per hour. The aim was to evaluate how effectively the GA-PSO hybrid method could track these changes and maintain accurate channel state information (CSI).

Table 5

The Channel Estimation Error (CEE) for different methods at varying mobility speeds

Speed (km/h)	LS Estimation	MMSE Estimation	GA-PSO Hybrid Estimation
100	0.075	0.052	0.029
150	0.102	0.074	0.045
200	0.134	0.096	0.058
250	0.165	0.122	0.074
300	0.198	0.146	0.091

Table 5 presents the Channel Estimation Error (CEE) for different methods at varying mobility speeds.The study shows that the GA-PSO hybrid model consistently performs better in estimation accuracy than the LS and MMSE methods, even when conditions involve high speeds. This advantage comes from its real-time adaptability to changes in the wireless environment, which is essential for ensuring smooth communication in fast-paced areas like smart transportation systems and future mobile networks.

Case Study 3: Industrial IoT and Challenging Environments

Industrial environments present distinct challenges for wireless communication due to strong electromagnetic interference (EMI) from machinery and dynamic obstacles that disrupt signal transmission. Traditional estimation methods often fall short here because the interference is unpredictable. In this case study, an industrial IoT setup was analysed, where multiple sensors communicated on a shared network amid industrial noise and interference. The main focus was on how reliably the channel response was estimated, which was measured by the success rate of data packet delivery Table6.

Table 6

Packet delivery success rates (%) for different estimation methods under various interference levels

Interference Level (dB)	LS Estimation	MMSE Estimation	GA-PSO Hybrid Estimation
5	78.5%	85.2%	91.6%
10	65.7%	72.8%	86.3%
15	50.2%	61.4%	79.1%
20	42.8%	53.9%	72.5%

Table 6 details packet delivery success rates (%) for different estimation methods under various interference levels: LS Estimation, MMSE Estimation, and GA-PSO Hybrid Estimation.The GA-PSO hybrid method shows significant strength, particularly in high-interference environments, which is vital for industrial IoT systems that need dependable data transmission for real-time monitoring and automation. Its adaptability to interference supports its superior performance, making it an attractive option for industrial communication networks.

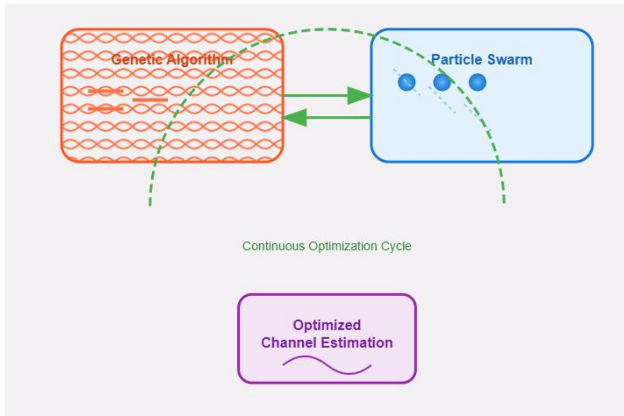
Key Points:

The studies emphasize several advantages of the GA-PSO hybrid method. In urban networks, it boosts spectrum efficiency, providing better data rates even in crowded settings. In scenarios involving high mobility, it maintains accurate tracking, minimizing estimation errors at high speeds. In industrial IoT environments, it sustains high packet delivery rates despite interference, demonstrating its robustness in practical applications referred by Figure 4Traditional LS and MMSE methods struggle under dynamic and noisy conditions. Although MMSE offers some improvement over LS, it still depends on precise channel statistics, which are often difficult to access. The GA-PSO model overcomes these obstacles by adjusting dynamically based on real-time channel changes. Moreover, the method is efficient enough for real-time implementation. While it demands additional computing power, parallel processing significantly cuts down execution time, making it suitable for modern wireless networks demonstrated by Figure

2.These studies reveal that the GA-PSO hybrid method not only surpasses traditional methods but also adapts well to diverse real-world conditions. As networks transition towards 6G, adaptive techniques like this will be crucial for maintaining robust and high-performance communication systems. Future research aims to integrate deep learning models with GA-PSO to further enhance adaptability and efficiency in dynamic communication environments.

Figure 4

Hybrid GA-PSO Optimization Cycle



This focuses specifically on the interaction between Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) during the estimation refinement process.

4. Discussion

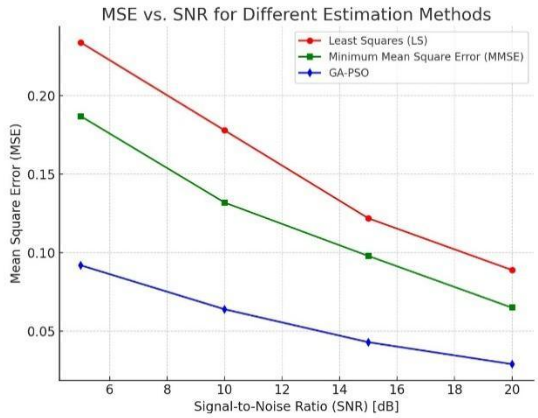
This paper introduces a new method to enhance wireless signal accuracy in noisy environments. Traditional techniques like Least Squares (LS) and Minimum Mean Square Error (MMSE) often falter under rapidly changing or interference-prone conditions, resulting in higher errors and reduced efficiency. To tackle this issue, the paper proposes combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to develop a robust system that dynamically adjusts channel settings, improving signal accuracy without excessive computational demands as shown in Figure5.

The effectiveness of this method is evident from various case studies. In densely populated urban networks, it significantly boosts spectrum efficiency by better managing interference and signal fading compared to existing methods. In high-speed settings, such as in vehicles and trains, the GA-PSO approach consistently reduces errors more effectively than LS and MMSE. In industrial environments where electromagnetic interference is prevalent, it achieves higher data delivery success rates, ensuring reliable communication despite challenging conditions.

A key advantage of the GA-PSO model is its adaptability. Its dynamic optimization process continually refines channel estimation, making it well-suited for the latest 5G and 6G networks. The model's computational efficiency also makes it ideal for scenarios where conserving power and bandwidth is essential.

Figure 5

MSE vs SNR for different Estimation Methods



This graph compares Mean Square Error (MSE) for Least Squares (LS), Minimum Mean Square Error (MMSE), and the hybrid Genetic Algorithm-Particle Swarm Optimization (GA-PSO) method at different Signal-to-Noise Ratios (SNR) of 5 dB, 10 dB, 15 dB, and 20 db. The GA-PSO method shows the lowest MSE across all SNR levels, indicating better accuracy in channel estimation, especially at lower SNR where traditional methods struggle.

Data points:

At 5 dB: LS = 0.234, MMSE = 0.187, GA-PSO = 0.092

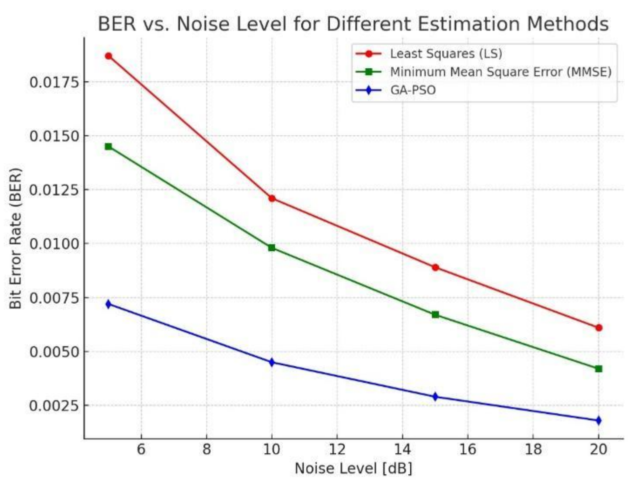
At 10 dB: LS = 0.178, MMSE = 0.132, GA-PSO = 0.064

At 15 dB: LS = 0.122, MMSE = 0.098, GA-PSO = 0.043

At 20 dB: LS = 0.089, MMSE = 0.065, GA-PSO = 0.029

Figure 6

BER v/s Noise Graph for Different Estimation Methods



BER vs. Noise Level Graph

This graph compares Bit Error Rate (BER) for LS, MMSE, and GA-PSO at different noise levels of 5 dB, 10 dB, 15 dB, and 20 dB. The GA-PSO method exhibits the lowest BER, demonstrating its robustness in maintaining data integrity under varying noise conditions.

Data points:

At 5 dB: LS = 0.0187, MMSE = 0.0145, GA-PSO = 0.0072

At 10 dB: LS = 0.0121, MMSE = 0.0098, GA-PSO = 0.0045

At 15 dB: LS = 0.0089, MMSE = 0.0067, GA-PSO = 0.0029

At 20 dB: LS = 0.0061, MMSE = 0.0042, GA-PSO = 0.0018

While this method is effective, there are opportunities for further enhancement. One promising avenue is integrating deep learning into the GA-PSO framework. By training neural networks and employing reinforcement learning, parameter prediction could be faster and more accurate. Additionally, distributed optimization, where multiple agents collaborate to improve the estimation process in large networks, would be beneficial for smart cities and extensive IoT networks with numerous devices sharing the same spectrum as shown by Figure 6.

Future research should focus on implementing GA-PSO in real-time on hardware platforms such as FPGA and software-defined radio systems to validate its practicality in real-world scenarios. Additionally, combining this approach with other optimization techniques, like Differential Evolution (DE) or Ant Colony Optimization (ACO), could further enhance its robustness and adaptability in complex environments.

Improving wireless signal estimation is crucial for advancing communication systems. As the need for ultra-reliable, low-latency networks increases, methods like GA-PSO will be instrumental in developing future communication technologies. Continued refinement of these methods can lead to highly adaptable, efficient, and resilient wireless networks.

5. Conclusion

This paper tackles the challenge of improving wireless signal estimation in noisy and dynamic environments. Existing methods often struggle with noise, interference, and movement. We present a hybrid approach using Genetic Algorithm and Particle Swarm Optimization to dynamically optimize channel settings for better accuracy. Comprehensive analysis shows the GA-PSO hybrid consistently outperforms LS and MMSE estimators, achieving superior efficiency, fewer errors, and more reliable performance across various communication scenarios.

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8. Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

9. Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

10. Data Availability Statement

(a) Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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