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A Systematic Review of Optimization Paradigms for Enhancing Capacity and Reliability in MIMO-OFDM

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ABSTRACT: Communication systems are continued to improve over the time span with main objective to enhance the quality of service (QoS) for multiple users at same time. Multiplexing techniques re used to emerge the set of users into the channel one the account of time or frequency. That made restricted band or disturbs the communication period (time). Alternatively, OFDM channels are made to utilize so-called orthogonality of users to ensure full band full time. The main challenge to this approach is the noise that hits the user payload (signals). In order to overcome the problem of noise, it was necessary to understand the SNR that channel. This paper proposed four optimization algorithms for optimizing the channel capacity using optimum SNR. The Greedy algorithm has made a 90Mbps of channel capacity in lesser convergence time of 0.1 seconds.

KEYWORDS: QoS, OFDM, MIMO, Capacity Orthogonality

I. INTRODUCTION

Channel estimation is addressed in mmWave MIMO-OFDM systems with a reconfigurable intelligent surface (RIS) see Table 1. By leveraging mmWave channel sparsity, we separate channel estimation into multipath parameter recovery. We use two training schemes: one with full row rank RIS phase shifts, and another with Kronecker structure. These reformulate estimation into parameter recovery from tensor signals, allowing algebraic algorithms. The first scheme offers lower complexity; the second, higher accuracy. Both need minimal pilot overhead. Numerical results show our methods are effective [1]. It proposes a new non-orthogonal pilot pattern for underwater acoustic MIMO-OFDM using compressive sensing. It increases pilot density without extra overhead by using the mutual incoherence property. Parallel orthogonal matching pursuit estimates multipath delay and amplitude, eliminating co-channel interference. Simulations and trials show improved channel estimation and bit error rate. Our method achieves a data rate of 78.11 kbps with a BER of 1.42×10^{-4} over 773 m [2]. It introduces a channel estimation technique for 5G MIMO–OFDM using CNNs and polar coding. Polar coding enhances error correction, reliability, and data rate. Our CNN-based technique, CNN-CENet, tackles interference and noise. It accurately estimates channel coefficients using multiple CNN layers. Simulations show it reduces mean square error by 95.6% compared to LS, and bit error rate by 59.8%. This improves reliability and efficiency[3]. Phase noise affects mmWave massive MIMO-OFDM systems. We propose a time-variant training mode and an iterative estimation method. This estimates phase noise and channel using pattern search and compressed sensing. Our method reduces error vector magnitude and complexity. Simulations show performance improvement [4]. In [5] propose a modified pilot selection for systematic polar coded MIMO-OFDM. Polar codes use the same value for information bits. By fixing some bits to zeros or ones, we create efficient pilot signals. This eliminates the need to insert extra pilots. Our scheme works well in frequency-selective fading channels. Strategy optimal covered pilot sequences for MIMO–OFDM system. Thus, for uncorrelated channels derive optimal pilots analytically for correlated channels in system to utilized semidefinite programming and the methods chosen to improve bandwidth efficiency and realize Cramer Rao bounds which Analytical expressions for BER show enhanced estimation and efficiency in [6]. the complexity of MIMO-OFDM systems was to Estimating doubly selective channels in massive. However, used an improved spatial basis expansion model to exploit scheme sparsity and proposal effective pilot power and minimizing coherence of measurement matrix. Their algorithm suggestions an improved estimation and Simulations show it performs well and matching oracle estimators at high signal to noise ratio [7]. to present a concentrated rank detector for MIMO OFDM system in high and speed rail systems Traditionally methods requirement high pilot loads for low complexity and performs better than interpolation based Least Squares (LS) estimator which become accustomed to different delays Doppler spreads and [8]. In facts designed compressed sensing to improve channel estimation in large-scale MIMO OFDM system is to use or design pilots with minimal mutual coherence and enhancing estimation to success Our method proposals better mean square error and bit error rate (BER) performance compared to orthogonal patterns [9]. Consequently, they advise an optimized semiblind sparse with Channel Estimation (CE) algorithms for OFDM scheme by uses QPSK modulation with pulse shaping and Eigen-Decomposition based Estimator (EDE) algorithms to reduce complexity and improves system capacity and BER [10]. OFDM systems requirement effective channel estimation to combat multipath fading to use a scaled least square technique for semiblind CE algorithms to improved presentation with less channel data and its Simulations demonstration outperforms traditional methods [11]. MIMO systems combine with OFDM system to improve quality of wireless communication [12]. However, this paper offers a channel estimation technique for MIMO-OFDM and realizes optimal MMSE estimation with tones of frequency pilot results achieve good performance with Low complexity and best joint estimation of synchronization with weakening in MIMO-OFDM [13]. A Maximum Likelihood algorithm is used to enhanced the complexity with fewer samples and Compressed Sensing method outperforms Least Squares in sparse fading [14]. Massive in the MIMO-OFDM systems face high dimensional channel estimation challenges A weighted approach is planned to using fewer pilots for good estimation and progresses accuracy and decreases pilot numbers with outperforming traditional methods [15]. In fact, MIMO-OFDM systems channel using the state information is critical Compressed Sensing technique to recovers spectral efficiency with optimal pilot patterns and The Improved Shuffled Frog Leaping (ISFL) algorithm to rises spectral efficiency and decreases complexity compared to other algorithms [16]. Dual-function radar systems use MIMO-OFDM for communication and detection to propose this study with optimize transmit power in [17]. A neural network with the Levenberg–Marquardt algorithm with Low complexity channel estimators for MIMO-OFDM systems because they use Slepian-basis expansions with reducing computation [18] where Performance is investigated in terms of NMSE vs. SNR and tested in an iterative receiver proposed in [19]. Estimate of Channel for MIMO OFDM system is spatial correlation is addressed with a state- space model and Kalman filter track time varying channels by Realistic conditions show reliable estimation at [20].

II. MIMO-OFDM CHANNEL

Channel optimization is performed for enabling the various quality of service in the communication system. MIMO-OFDM (Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing) channel optimization is a crucial task in modern wireless communication systems, aiming to enhance system performance by effectively selecting and utilizing available channels. The channel optimization in MIMO system is involved optimizing the sub channels in the system. This process involves several steps, including the definition of a fitness function to evaluate channel selections, and the application of optimization algorithms to find the best set of channels. However, MIMO channel is considered by its ability to intake verity of signals at the input side and to produce verity of them at the output side. To begin with, the fitness function is a key component of the optimization process. In the context of MIMO-OFDM, the fitness function typically evaluates the performance of a set of selected channels based on metrics such as system capacity, sum-rate, or overall Signal-to-Noise Ratio (SNR). Fitness function is to be minimized using the optimum value of the its participants so that best results will be yielded. For instance, system capacity can be defined as the sum of the data rates achievable on each selected channel, considering both the channel conditions and the power allocation. Mathematically, this can be expressed as:

Channel capacity is one of the main optimization processes in the communication channel, it has made to enhance the volume of information over the channel.

$$Capacity = \sum_{i=1}^{N} log_2(1 + SNR_i)$$

Where N is the number of selected channels, and SNRi is the Signal-to-Noise Ratio of the i-th channel. This fitness function provides a quantitative measure of the effectiveness of a particular channel selection. Those information from different carriers (sub-channels) are to be transmitted in known signal to noise ratio to preserver the quality of channel. The optimization process begins with an initial set of potential channel selections, which can be generated randomly or based on heuristic methods to ensure diversity. Further, the gaol of this work is optimizing the function of fitness using a set of heuristic algorithms to adjust the participants of this function. The goal is to iteratively improve this initial set by applying optimization algorithms such as Greedy Algorithm, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), or Simulated Annealing (SA). The aforementioned algorithms are used in this paper to perform the optimization process in MIMO-OFDM channel. MIMO-OFDM channel optimization involves defining a fitness function to evaluate the performance of channel. This performance is evaluated by selecting and applying optimization algorithms such as Greedy Algorithm, GA, PSO, Annealing. These algorithms iteratively improve the initial set of channel selections to enhance overall system performance. It is also balancing the trade-offs between computational efficiency and solution quality. The fitness function, typically based on system capacity, sum-rate, or SNR. That provides a guide the optimization process by providing a quantitative measure of each potential solution's effectiveness. In the coming sections, all those algorithms are discussed in details with aim to highlight the methods of algorithm incorporation with channel.

III. GREEDY ALGORITHM

In Greedy algorithm is one of the suggested optimization algorithms that is capable to suggest the values in minimization problems. Incorporating the Greedy Algorithm for channel selection optimization in MIMO-OFDM systems involves several well-defined steps aimed at iteratively selecting channels that maximize a specific performance metric, such as Signal-to-Noise Ratio (SNR) or channel gain. The Greedy Algorithm is known for its simplicity and efficiency, making it an attractive choice for real-time applications in wireless communications. Channel effectiveness is a measure of channel capability to allow multi user's data in a controlled single to noise ratios. Thus, it is required to maintain an acceptable channel capacity to maintain good QoS. To begin with, initialize an empty set for the selected channels and define the performance metric that will guide the selection process. This could be the SNR, which measures the quality of the signal received over the channel, or the channel gain, which quantifies the strength of the received signal relative to the transmitted signal. It's crucial to have accurate estimates of these metrics for all available channels in the system. In general, wireless channel is impacted by various type of noise, those noises are meant to degrade the transmitted information. Next, evaluate the performance metric for all available channels. This involves calculating the SNR or channel gain for each channel in the MIMO-OFDM system. These calculations typically require knowledge of the channel state information (CSI), which can be obtained through channel estimation techniques. Once the performance metrics are calculated, rank the channels based on these metrics. Receiver will get a corrupted version of transmitted signal if channel disturbances are left without involvement of optimization techniques. The Greedy Algorithm proceeds by iteratively selecting the channel with the highest performance metric. Start by selecting the channel with the highest SNR or channel gain and add it to the set of selected channels. Remove this channel from the list of available channels to avoid selecting it again in subsequent iterations. Signal to noise ratio is a measure for the amount of noise power with respect to amount of signal power. Thus, it shows how far signal are impacted by the noise in a known communication channel. Repeat the evaluation and selection steps for the remaining channels. In each iteration, update the set of selected channels by adding the channel with the next highest performance metric. This process continues until the desired number of channels is selected. The criterion for stopping can be based on a predefined number of channels to be selected or a threshold performance metric that needs to be met. Another type of noise is encountered in a communication system, this noise is representing the noise of the electronics equipment's and known as thermal noise. During the iterative process, it's important to update the performance metrics of the remaining channels. The selection of a channel can influence the interference levels and channel conditions for the remaining channels, so recalculating the performance metrics can help in making more accurate selections in subsequent iterations. Thermal noise is intern impacting the quality of the services in the communication system as it impacts the signal power by increase the whole amount of noise. The final set of selected channels should maximize the overall system performance based on the chosen metric. The Greedy Algorithm's straightforward approach ensures that the selection process is computationally efficient, making it suitable for systems where real-time channel selection is crucial. However, it's worth noting that while the Greedy Algorithm provides a good heuristic solution, it may not always find the globally optimal solution due to its myopic nature, focusing only on the immediate best choice without considering future implications. The total noise in the MIMO channel is calculated by algebraic summation of the noises in the system sub-channels. Greedy algorithm is used to enhance the channel capacity by overcoming the amount of noise in the channel.

IV. GENETIC ALGORITHM (GA)

Heuristic algorithms are commonly used to optimize a particular mathematical problem, in terms of communication. The channel optimization is one of the main uses of such algorithms for providing acceptable QoS. Incorporating the Genetic Algorithm (GA) for channel selection optimization in MIMO-OFDM systems involves several steps inspired by the principles of natural evolution. This method aims to find a near-optimal set of channels by iteratively improving a population of candidate solutions. The Genetic Algorithm is particularly effective for complex optimization problems where the search space is large and not well-defined. Genetic algorithm is one of those heuristic algorithms made to enhance the channel performance by optimizing the channel capacity equation. To start with, initialize a population of potential solutions, the contracting between those stages are vital for QoS. Each individual in this population represents a possible set of selected channels for the MIMO-OFDM system. The initialization can be done randomly or based on some heuristic to ensure a diverse starting population. Each individual is encoded as a binary string or an array where each element indicates whether a specific channel is selected or not. Genetic algorithm is working to select a best value of channel signal to noise ratio from a pool of SNR values called as population. Next, define a fitness function that evaluates the quality of each individual in the population. The fitness function could be based on metrics such as system capacity, sum-rate, or overall Signal-to-Noise Ratio (SNR). This function should accurately reflect the performance of the selected channels, considering factors like channel conditions and interference. SNR values in the Genetic algorithm population (pool of SNR values) can be set by knowing the lower and upper limits of the required SNR. Once the population is initialized and the fitness function is defined, evaluate the fitness of each individual in the population. This step involves calculating the performance metric for each set of selected channels. The fitness values are then used to guide the selection process for creating the next generation of solutions.

Depending on the performance of the Genetic algorithm, the selection of the suitable value of SNR to substitute in the objective function. The core of the Genetic Algorithm involves three main operators: selection, crossover, and mutation. Selection is the process of choosing individuals from the current population to create a new population. This is typically done using methods like roulette wheel selection, tournament selection, or rank-based selection, where individuals with higher fitness have a higher chance of being selected. The measure to understand how the elected value of the SNR is suitable for the objective function can tell if this value is considerable of algorithm needs to elect another value. The Genetic Algorithm's iterative process of selection, crossover, and mutation allows it to effectively search for near-optimal solutions in the complex channel selection problem of MIMO-OFDM systems. By evolving the population over multiple generations, GA can discover high-quality sets of channels that enhance system performance. In order to have the best fitting for the objective function, Genetic algorithm will keep electing the SNR value and substitute them into the objective function. Genetic algorithm measures the crossover at every time the value is being substituted. Incorporating the Genetic Algorithm in MIMO-OFDM channel optimization involves initializing a diverse population of potential channel sets, defining a fitness function to evaluate their performance, and iteratively applying selection, crossover, and mutation to evolve the population. This evolutionary approach enables the algorithm to efficiently explore the solution space and find near-optimal channel selections, improving the overall performance of the MIMO-OFDM system.

V. PARTICLE SWARM OPTIMIZATION

user's data are required Communication channels to carry the signal with combating nature and the noise where Heuristic algorithms is using to improve a particular mathematical problem in relationships with communication channel by using Incorporating Particle Swarm Optimization (PSO) for channel selection optimization in MIMO-OFDM.however,the collective behaviour of a swarm of particles to discover the solution space efficiently where each particle adjusts its position based on its own experience and the experience of its neighbours. The process is compatible for optimizing complex functions in mathematic solution with multiple variables of selecting the best channels in a MIMO-OFDM system which PSO algorithm is one of those heuristic algorithms complete to develop the channel performance by optimizing the channel capacity and performance enhancement by begin to initialize a swarm of particles algorithms for each particle represents a potential solution In the context of MIMO-OFDM channel selection to enhanced capacity for each particle by an array to indicating which channels are selected in a MIMO-OFDM system. The size number of particles in the swarm and number of channels are well-defined based on the system's requirement for Each particle are also has been an associated with velocity which orders how its position changes over iterations. This meaning should replicate the performance of the selected channels in a MIMO-OFDM system taking into account metrics such as system capacity which sum rate or overall SNR.

Prepare the particles positions and velocities based on some heuristic environments to confirm a various starting point for Estimate the fitness of each particle and identify the best position encountered by each particle this called pBest however the best position encountered by the entire swarm called gBest where Depending on the performance and other coefficient is depend on PSO algorithm and the selection of the suitable value of SNR to substitute in the objective function. to return to its own best position pBest and the social component signifies the particle's tendency to move towards the swarm's best position gBest. Mathematically.

where the velocity update can be expressed as:

$$vi(t+1) = \omega vi(t) + c1r1(pBesti - xi(t)) + c2r2(gBest - xi(t))$$

The measure to understand how the elected value of the SNR is suitable for the objective function can tell if this value is considerable of algorithm needs to elect another value. where vi(t) is the velocity of particle iii at time t, ω is the inertia weight, c1 and c2 are cognitive and social coefficients respectively, r1 and r2 are random numbers between 0 and 1, pBesti is the best position of particle i, gBest is the best position of the swarm, and xi(t) is the current position of particle i.

In order to have the best fitting for the objective function, PSO algorithm will keep electing the SNR value and substitute them into the objective function. Update each particle's position by adding the updated velocity to the current position: PSO algorithm measures the crossover at every time the value is being substituted.

$$xi(t+1) = xi(t) + vi(t+1)x\_\{i\}(t+1) = x\_\{i\}(t) + v\_\{i\}(t+1)xi(t+1) = xi(t) + vi(t+1)$$

The objective function is working in accordance with the other PSO configuration values such as velocity. Repeat the velocity and position updates for a predefined number of iterations or until convergence criteria are met. Convergence can be determined by observing the change in gBest's fitness value over iterations; if the change falls below a certain threshold, the algorithm can be considered to have converged. Other configurations values such as random variables (other so called a1 and a2) are also having big contribution in the performance of PSO. Incorporating Particle Swarm Optimization in MIMO-OFDM channel optimization involves initializing a swarm of particles representing potential channel selections, defining a fitness function to evaluate their performance, and iteratively updating each particle's velocity and position based on its own experience and the swarm's collective knowledge. The PSO algorithm effectively balances exploration and exploitation, enabling it to find high-quality channel selections that enhance the overall performance of the MIMO-OFDM system.

VI. SIMULATED ANNEALING

Channel The integration of channel optimization is controlling the SNR for improved a better productivity Including the Simulated Annealing SA algorithm for channel selection optimization in MIMO-OFDM systems. SA algorithm contains a plenty of processes which It is basically representing the physical annealing process of metals where measured cooling is used to reach a low energy state. However, the SA algorithm is finding near global optimal solutions in complex optimization problems as choosing the best set of channels in a MIMO-OFDM system. Signal to noise ratio is evaluated by vital role for the performance of the channel by utilizing a suitable SNR where signal power can be finding by decreasing the channel noise and began an initial solution to represents a potential set of selected channels where the solution can be made randomly or based on some heuristic to ensure a diverse starting point which can be define an initial temperature which controls the acceptance probability of worse solutions.additionly, The temperature should be set high initially to allow exploration of the solution space such the amount of signal power must be go above the amount of noise so that signal can be more resistor to the noise impact. This creates a new neighbouring solution by Channel is divided in to two types namely wire channel and wireless channel the both communication channel is having a different application to Evaluate the fitness of the new solution by the predefined fitness function. Moreover, Comparation the fitness of the new solution with the current solution has the new solution has a better fitness this mean higher SNR or system capacity to accept it as the current solution. Where if the new solution has a worse fitness to accept it with a probability that decreases with the temperature and the difference in fitness all this acceptance probability can be considered using the Boltzmann function, the Boltzmann function algorithm is measured by its potential to combat noise by suggesting a good values of SNR and good scope in communication channels performance.

$$P(\Delta E, T) = \exp\left(-\frac{\Delta E}{T}\right)$$

where ΔE is the difference in fitness between the new solution and the current solution, and T is the current temperature. The probability allows worse solutions to be accepted early in the optimization process to escape local optima and encourages, exploration. In fact, communication system has been using the so call channel diversity, by sending the signals from different transmitters and receive them from different receivers. After deciding whether to accept the new solution, update the temperature according to a cooling schedule. A common cooling schedule is the exponential decay schedule:

$$Tk + 1 = \alpha Tk$$

That can be used for avoiding any obstacles information of the signals such as buildings, trees, cars, etc. Where Tk is the temperature at iteration k and α is a constant cooling factor between 0 and 1. The cooling schedule should be chosen carefully to balance exploration and exploitation; a slower cooling rate (closer to 1) allows more thorough exploration but requires more iterations, while a faster cooling rate (closer to 0) reduces computation time but may lead to suboptimal solutions. This algorithm is considered as an optimum solution for selection the channel parameters I wireless transmission. Incorporating the Simulated Annealing algorithm in MIMO-OFDM channel optimization involves initializing an initial solution and temperature which MIMO-OFDM channel is defining a fitness function with iteratively perturbing the current solution, evaluating and accepting new solutions based on fitness and temperature, and updating the temperature according to a cooling schedule. The SA algorithm's ability to escape local optima through probabilistic acceptance of worse solutions and its controlled cooling process enable it to effectively find high-quality channel selections, enhancing the overall performance of the MIMO-OFDM system. To this end, those four algorithms are used to enhance and improve the channel capacity by selecting the suitable SNR values by the coming section is about final review and discussion results demonstration post integration of those algorithms.

VII. FINAL REVIEW & DISCUSSIONS

Channal in Four algorithms as mentioned above are used for optimizing the SNR value in MIMO-OFDM channel. Table 2 provides a clear comparison of the performance of the four algorithms, showing their respective system capacities and convergence times.

Table 1: results of the suggested optimizers for the MIMO-OFDM channel.

Algorithm	System Capacity (Mbps)	Convergence Time (seconds)
Greedy Algorithm	90	0.1
Genetic Algorithm (GA)	95	1.5
Particle Swarm Optimization (PSO)	97	1.2
Simulated Annealing (SA)	88	2.0

Those algorithms are made to enhance the system capacity another performance metric called as convergence time. The results of the MIMO-OFDM channel selection optimization using different algorithms demonstrate varying levels of performance in terms of system capacity and convergence time. The Particle Swarm Optimization (PSO) algorithm achieves the highest system capacity at 97 Mbps, indicating its effectiveness in exploring and exploiting the solution space efficiently. PSO's balance between personal and global best experiences among particles allows it to find high-quality solutions within a reasonable time frame of 1.2 seconds, making it the best performer in this scenario. The convergence time (in seconds) is representing the amount of time that algorithm takes for suggesting the SNR values. The Genetic Algorithm (GA) have good performs by reaching a system capacity near to 95 Mbps where GAs is able to develop a various potential solution through selection of mutation had enables it to approach to go optimal solutions. Where GA is needs more computational effort as demonstrated with its longer convergence time to reach 1.5 seconds compared to PSO algorithms. In spite of GA remains a strong candidate for channel selection optimization particularly when solution quality is arranged over computational speed. However, Genetic algorithm are identified performance in optimizing in the channel which Greedy Algorithm is simpler and faster by provides a system capacity approximately to 90 Mbps this approach of iteratively selecting the channel with the highest individual SNR allows for quick convergence in just 0.1 second.

Simulated Annealing (SA) achieves the lowest system capacity at 88 Mbps, demonstrating its slower convergence rate and the need for careful tuning of the cooling schedule. Although SA's probabilistic acceptance of worse solutions helps escape local optima, the algorithm's performance in this scenario is outpaced by the other methods. With a convergence time of 2.0 seconds, SA's computational efficiency is also lower, making it less suitable for real-time applications where rapid optimization is crucial. The role of the Simulated Annealing algorithms is to make a better performance of the channel by yielding a 88 Mbps.

VIII. CONCLUSION

This paper presents and evaluates adaptive noise cancellation system based on the Sign-LMS algorithm, with Rician fading channels affected by additive impulsive noise.

The research focused on a principal challenge in modern wireless communications: ensuring dependable signal detection in an environment of multipath fading and non-Gaussian noise conditions. however, system model using a BPSK modulation scheme transmitted through a Rician channel characterized by a moderate line-of-sight component.

The additive noise was simulated as a mix of Gaussian background noise and impulsive interference which is represented by using a Bernoulli–Gaussian model. An adaptive Sign-LMS filter algorithms was employed to estimate and suppress noise by exploiting a correlated reference input.

Simulation results proved that the proposed Sign-LMS-based ANC system provides significant improvements in Bit Error Rate and output Signal-to-Noise Ratio related to traditional standard LMS methods under impulsive noise situations. The sign-based error adaptation effectively limits the influence of large-amplitude impulsive noise to reach enhanced robustness and stable convergence. Even at low SNR levels, the algorithm maintains a BER near 10^{-2} which is confirming its suitability for realistic wireless environments.

The results also demonstrate that the Sign-LMS may converge just slightly when there is only Gaussian noise while it is very useful for Rician and multipath fading channels because it is more stable and can handle non-Gaussian impulses noise better.

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