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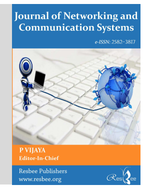

Hybrid PSO-GSA Algorithm for Channel Estimation in Massive MIMO System

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Abstract: For advanced communication MILLIMETER wave (mmWave) is represented as a buoyant technology against wireless networks because of its prosperous frequency spectral resources in Multiple Input Multiple Output (MIMO). Nevertheless, the mmWave is diagnosed in MIMO remnants as a complex task that appears as the problems such as maximized propagation loss. Hence, this work introduces a novel optimization helped-out estimation technique to calculate the mm-wave channel parameters. On mm-wave massive MIMO system the performance of hybrid precoding, as well as channel estimation, is developed through using optimization procedure in codebook model principles. In reality, existing models are carried out the uniform distribution of azimuth angles in the codebook model, the wherein developed method estimates it as a single objective optimization issue without contravening characteristics of angle. To resolve the aforesaid optimization issue, the Hybrid Particle Swarm Optimization (PSO)- Gravitational Search Algorithm (GSA) technique is developed which hybridizes the idea of PSO and GSA method correspondingly. At last, the developed model performance is evaluated and examined with the conventional methods regarding the Channel State Information (CSI) and error metrics.

Keywords: CSI, Codebook Introduction, MIMO, Mm Wave, Precoding,

Nomenclature

Abbreviations	Descriptions
MS	Mobile Station
TDD	Time Division Duplex
BS	Base Station
mMIMO	Massive Multiple Input Multiple Output
ULA	Uniform Linear Array
CSI	Channel State Information
PSO	Particle Swarm Optimization
DFT	Discrete Fourier Transform
GSA	Gravitational Search Algorithm
SSR	Sparse Signal Recover
VBI	Variational Bayesian Inference
FDD	Frequency Division Duplex
SoI	Signal-of-Interest
LSE	Least Squares Estimation
GC	Gaussian-Categorical

1. Introduction

Nowadays, wireless throughput is considered a raising requirement when the available electromagnetic spectrum does not alter. Hence, the MIMO is represented as an optimistic technology that produces maximum throughput wireless communication available [1]. The base stations of massive MIMO contain a huge amount of antennas that concurrently act as users with one or a minimum amount of antennas. In preferred directions, higher antenna arrays have the ability to produce a more focused beam. By pre-coding the signals the beam focusing is carried out which is related to a particular user. Moreover, in BS, the CSI should be known to carry out the pre-coding. Conversely, for precise detection, the CSI is needed in the receiver of both Mobile MS and BS. Hence, for the estimation of CSI with maximum precision, it is very important [2]. Moreover, the estimation of the uplink CSI information is simpler than the downlink

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channel. Diverse users transmit more data streams to the BS in the uplink, as well as BS with dominant computational capability, has the ability to calculate the CSI consistently. By exploiting the uplink estimated channel the Downlink CSI can be attained as well as channel reciprocity property directly in massive MIMO systems with TDD protocol. However, it is exhibited that hardware mutilation has the ability to corrupt the estimation of channel precision in TDD Massive MIMO systems [1].

The estimation of the channel includes channel coefficients estimation in proportion to input-output antennas each pair, each and every one placed in concert in a matrix that is known as the channel matrix in a MIMO system [12]. In order to attain this matrix the most familiar manner is to transmit a training series, so, forgoing a transmission rate fraction. Conversely, because of the sudden alterations of the channel, the tracking or training of the channel might be infeasible. Here, the transmitted data can be differentially encoded which is considered as one of the probable solutions and hence eradicate the necessity for channel information. The alternate method is to use the well-known properties of transferred data to study channels blindly that is known as blind channel estimation [2].

In the massive MIMO channel, several studies have shown that the elements are extremely correlated as well as the efficient dimension is greatly lesser than the original dimension. It is due to the restricted amount of scatters in the propagation environment. On the whole, if Base Station is prepared by means of a huge number of ULA, the massive MIMO channel has a roughly sparse illustration on DFT basis. Nowadays, by means of using such hidden sparsity, a large number of downlink channel estimation, as well as feedback methods, were developed. However, for DFT-based channel estimation techniques, there are two disadvantages such as they undergo performance loss because of the energy leakage that occurred by direction mismatch. Also, they are only accessible to ULAs due to DFT basis is based upon ULAs special structure [3].

The main contribution of this work is to propose precoding as well as channel estimation performance on mm-Wave m-MIMO using the optimization procedure in the codebook. In the uniform distribution of azimuth angles, when the existing methods have been performed in the codebook design, the developed model devises the single objective optimization issue without contravening the characteristics of the angle. Hence, a hybrid PO-GSA optimization model is proposed to solve the aforesaid issue.

2. Literature Survey

In 2021, Rong Dai et al [1], worked on a channel estimation technique on the basis of minimized dimension decomposition. To attain a primary sparse support set SSR model was exploited. Subsequently, the adjustment parameter was referred to as the off-grid error. The true discrete grid was exploited by Taylor's formulation and also an orthogonal relationship was exploited among the noise and signal subspace. At last, the LSE method was used to estimate the path gain.

In 2020, N. Shalavi et al [2], modeled the FDD massive MIMO downlink frequency selective channel estimation. An appropriate pilot series was modeled for the developed technique; also an estimation model was presented related to this technique to resolve the issue. Finally, the developed technique possesses superior Bit Error Rate performance than the conventional techniques in a similar pilot overhead ratio.

In 2020, Zaid Albataineh et al [3], proposed a new channel estimation method as a mean of reducing the issues related to pilot overhead. On the basis of the integration of compressive sampling as well as sparsity, adaptive matching was exploited by the developed model. With respect to the spatial correlations, in MIMO systems the signal sources were sparsely distributed. This distribution pattern set up subsequently exploits the compressive sampling models to resolves the estimation of channel issue in MIMO systems.

In 2020, Kamran Kalbasi and S. Jamaloddin Golestani [4] addressed the maximum-likelihood channel estimation by means of orthogonal space-time block codes while finite alphabet restraint of the signal constellation was relaxed for MIMO systems. Moreover, the estimation of channel coefficients was studied and the subspace was also generated using the developed method. Then the subspace algebraic characterization was also provided that shows the issue in optimization into a simply algebraic one and significantly that tends to numerous motivating analytical proofs.

In 2019, Jisheng Dai et al [5] presented the VBI method to detach effects from the SoI as well as impulsive noise. Subsequently, an enhanced two-phase hierarchical prior to enforcing sparsity was introduced when assurance a denser impulsive noise against the SoI concurrently. Owing to developing the VBI detachment as well as the novel sparsity prior, the proposed technique has the ability to transport a substantial minimization of computational complexity and attain superior channel estimation precision.

In 2020, Xiantao Cheng et al [6], developed a hierarchical GC prior model for channel vectors to be calculated. The hyper-parameters related with GC prior were deceitfully coupled so that the GC model had possible to typify the deviating channel sparsity patterns besides the BS array.

3. System Model

Generally, BS comprises O_{BS} antennas as well as O_{RF} RF chains in order to communicate with a single MS. In general, MS's number of RF chains is lesser than BS's. The communication of BS and MS is done via O_S data streams, in that $O_S \le O_{RF} \le O_{BS}$ and $O_S \le O_{RF} \le O_{MS}$ [7].

The main objective of this work is to concentrate on downlink transmission. By BS a $O_{RF} \times O_S$ baseband pre-coder O_{BB} is presumed to be used subsequent $O_{BS} \times O_{RF}$ RF pre-coder, R_{RF}. If $R_L = R_{RF}R_{BB}$ is the $O_{BS} \times O_S$ combined BS pre-coding matrix, as per Eq. (1), the discrete-time signal transmitted can be devised. Eq. (1), P_S indicates the average total power that is transferred as well as r indicates the $O_S \times 1$ vector of symbols that are transferred, so that $E\left[rr^C\right] = \frac{P_S}{O_S} I_{O_S}$.

$$y = R_L r \tag{1}$$

Using analog phase R_{RF} is used, its ingress is ofconstant modulus. In order to satisfy $\left|[R_{RF}]_{m,n}\right|^2 = O_{BS}^{-1}$ these entries were normalized, that $\left|[R_{RF}]_{m,n}\right|$ indicates the magnitude of (m,n)th module of R_{RF}. The total power parameter can be enforced so that $\|R_{RF}R_{BB}\|_R^2 = O_S$ by normalizing R_{BB}.

A narrowband block-fading channel was used, as seen in eq. (2), MS notices the received signal. Where, C states the $O_{MS} \times O_{BS}$ matrix that identifies mm-Wave channel amid BS and MS, and $n \sim N\left(0, \sigma^2\right)$ indicates Gaussian noise weakening the received signal.

$$s = CR_L r + n \tag{2}$$

As seen in eq. (3), the combiner V_L consisting of the baseband combiners V_{RF} and V_{BB} and RF at MS is employed to process the received signal s. The same method could be used directly to uplink model as its input-output linked is equivalent to eq.(3) with C indicated by uplink channel, as well as combiners role (V_{RF}, V_{BB}) and pre-coders (R_{RF}, R_{BB}) switched.

$$x = V_L{}^C CR_L r + V_L{}^C n \tag{3}$$

In this paper, a geometric channel method with T scatterers is used as mm-Wave channels have limited scattering [8]. Then, each scatters is used to contribute a particular propagation path among the MS and BS. On the basis of this method, the channel C can be devised as in Eq. (4), whereas υ_l indicates a multifaceted increase of l^{th} path, ρ states average path-loss among the MS and BS, as well as ϖ indicates azimuth angle. The developed model is deal with accurate channel estimation, ϖ indicates optimally tuned by a new meta-heuristic algorithm.

$$C = \sqrt{\frac{O_{BS}O_{MS}}{\rho}} \sum_{l=1}^{T} \upsilon_l b_{MS}(\varpi_l) b_{BS}^C(\phi_l) \tag{4}$$

By presuming (Uniform Linear Arrays) ULAs, as per Eq. (5) $b_{BS}(\phi_l)$ can be devised, in that d indicate the distance among antenna components as well as λ indicates the signal wavelength. The MS $b_{MS}(\phi_l)$ indicates array response vectors that can be designed similarly. As in Eq. (6), Eq. (4) can be summarized and formulated, in that $\upsilon = \frac{\sqrt{O_{BS}O_{MS}}}{\rho}[\upsilon_1, \upsilon_{2,} .....\upsilon_T]^L$.

$$b_{BS}(\phi_l) = \frac{1}{\sqrt{O_{BS}}}\left[1, e^{j\frac{2\pi}{\lambda} d \sin(\phi_l)}, ... e^{j(O_{BS}-1)\frac{2\pi}{\lambda} d \sin(\phi_l)}\right]^L \tag{5}$$

$$C = F_{MS} \mathrm{dia}(\upsilon) b_{BS}^C \tag{6}$$

The matrices $F_{MS} = [b_{MS}(\varpi_1), b_{BS}(\varpi_2) .....b_{BS}(\varpi_T)]$ and $F_{BS} = [b_{BS}(\phi_1), b_{BS}(\phi_2) .....b_{BS}(\phi_T)]$ comprise the array response vectors of BS and MS.

4. Hybrid Precoding based on Multi-Resolution Hierarchical Codebook

In this paper, to design a multi-resolution BF codebook, a novel hybrid digital/analog-based, model is developed. For non-ULAs or ULAs to generate the BF vectors are widespread for the developed model that comprises minimum complexity as well as it carries out superior to the "analog-only beamforming codebooks". Nevertheless, in mm-Wave, many limitations are faced by the analog-only multi-resolution codebooks model.

The non-overlapping patterns of the beam are complicated by the quantized phase shifters hence it may require a systematic search against a large space with several antennas.

On the basis of ULA beam steering beam patterns, the model of analog merely BF vectors with particular, as well as it is restricted to be used for non-ULAs because it does not possess any knowledge concerning the beam patterns. The codebook design and structure for the simplified indication, the BS training precoding codebook $\Im$ model is fretful in this paper to model MS training codebook Γ.

As per Eq. (8), in every codebook level r, and subset o, BF vectors $\left[R_{(r,o)}\right]_{:,m}$, $m = 1,2.....K$ are designed whereas $\Re_{(r,o,m)}$ can be devised as stated in Eq. (7) that shows the AoD's sub-range associated with BF vector, $\left[R_{(r,o)}\right]_{:,m}$ as well as H_r states the normalization constants that gratifies $\left\|R_{(r,o)}\right\|_R = K$.

$$\Re_{(r,o,m)} = \left\{\frac{O}{K^r}\left(K(o-1)+m-1\right)+1,.....\frac{O}{K^r}\left(K(o-1)+m\right)\right\} \tag{7}$$

$$\left[R_{(r,o)}\right]^C_{:,m} b_{BS}\left(\bar{\phi}_u\right) = \begin{cases} H_r & \text{if } u \in \Re_{(r,o,m)} \\ 0 & \text{if } u \in \Re_{(r,o,m)} \end{cases} \tag{8}$$

In Eq. (8) $R_{(r,o)}$ can be reformulated as Eq. (9) in a compressed form, which $W_{(r,o)}$ shows an $O \times K$ matrix using each column *m* having 1's in positions $v, v \in \Re_{(r,o,m)}$ and 0's in positions $v, v \notin \Re_{(r,o,m)}$.

$$F^C_{BS,D} R_{(r,o)} = H_r W_{(r,o)} \tag{9}$$

For BS, the AoDs matrix $F_{BS,D}$ is an over whole lexicon with $O \geq O_{BS}$, which is, Eq. (9) shows a conflicting system, whereas the estimated solution is stated by $R_{(r,o)} = H_r\left(F_{BS,D}\, F^C_{BS,D}\right)^{-1} F_{BS,D} W_{(r,o)}$). At a certain time interval, every BF vector are separately used and hence, each of them will be modeled independently regarding the hybrid digital/analog pre-coders. Then, by exploiting the eq. (10), the design of the hybrid digital and analog training precoding matrices is attained, in that $\left[R_{(r,o)}\right]_{:,m} = H_r\left(F_{BS,D}\, F^C_{BS,D}\right)^{-1} F_{BS,D}\left[W_{(r,o)}\right]_{:,m}$, and F_{can} is an $O_{BS} \times O_{can}$ matrix that seizes the finite set of possible analog BF vectors.

$$\begin{aligned} &\left\{R^*_{RF(r,o)}, \left[R^*_{BB(r,o)}\right]_{:,m}\right\} = \arg\min \left\|\left[R_{(r,o)}\right]_{:,m} - R_{RF(r,o)}\left[R_{BB(r,o)}\right]_{:,m}\right\|_R \\ &\text{s.t}\left[R_{(r,o)}\right]_{:,j} \in \left\{\left[F_{can}\right]_{:,l} \middle| 1 \leq l \leq O_{can}\right\}, i = 1,2,..O_{RF} \\ &\left\|R_{RF(r,o)}\left[R_{BB(r,o)}\right]_{:,m}\right\|^2_R = 1 \end{aligned} \tag{10}$$

F_{can} denotes the candidate matrix columns which is chosen to satisfy the arbitrary analog BF parameters. During the experimentations, 2 representations of candidate BF models are considered are represented as follows.

a) For $t_{can} = 0,1,2....O_{can} - 1$ Uniformly spaced ULA beam steering vectors [9], which is; a group of O_{can} vectors in the type of $b_{BS}\left(\frac{t_{can}\pi}{O}\right)$.

b) The BF vector elements could be identified as quantized phase shifts, by an NQ-bit input if each phase shifter is regulated, the candidate entry pre-coding matrix F_{can} can be indicated as $e^{j\frac{o_Q 2\pi}{2^{O_Q}}}$ for certain $o_Q = 0,1,2......,2^{O_Q} - 1$.

By representing the matrix of feasible analog BF vectors F_{can}, in Eq. (10) the optimization problems can be redesigned as a sparse approximation problem [7].

$$\left\{\left[R^{*}_{BB,(r,o)}\right]_{:,m}\right\} = \arg\min \left\|\left[R_{(r,o)}\right]_{:,m} - F_{can}\left[R_{BB,(r,o)}\right]_{:,m}\right\| R,$$
$$\text{s.t} \quad \left\|\operatorname{diag}\left(\left[R_{BB,(r,o)}\right]_{:,m}\left[R_{BB,(r,o)}\right]^{C}_{:,m}\right)\right\| l_0 = O_{RF} \tag{11}$$
$$\left\|R_{RF(r,o)}\left[R_{BB,(r,o)}\right]_{:,m}\right\|^{2}_{R} = 1$$

In Eq. (11) the first parameter makes assure that merely O_{RF} rows of $\left[R_{BB,(r,o)}\right]_{:,m}$ can be non-0's. Hence, using this sparse problem subsequent to designing the baseband training1 pre-coder, the F_{can} columns indicate the non-zero rows of $\left[R_{BB,(r,o)}\right]_{:,m}$ are chosen to be RF precoder $R_{RF(r,o)}$. In Eq. (11) the accurate solution of the sparse approximation problems required to resolve an extremely complex combinatorial optimization problem.

Hence, subsequent [7], an orthogonal matching pursuit model is modeled to resolve this problem iteratively. Moreover, the constant H_r is not identified as apriori and it needs to be maximized preferably as it is proportional to the increase of BF as stated in Eq. (8). Nevertheless, in order to obtain a solution with minimum complexity, it is presumed as a constant, as well as its value is calculated subsequent to modeling the BF vectors to normalize them. Algorithm 1 exhibits the proposed estimation method.

Algorithm 1: Adopted Estimation method to Multipath mm-wave channels

Input: MS and BS be acquainted with O, K, T_d and possess $\Im$ and Γ, ϖ : $(0, 2\pi)$

Initialize : $L^{BS}_{(1,1)} = \{1,\ldots 1\}$, $L^{MS}_{(1,1)} = \{1,\ldots 1\}$, $S = \log_K (O / T_d)$

for $l \le T_d$

for $r \le S$ do

for $m_{BS} \le KT_d$ do

By BS a training symbol is transmitted by exploiting $\left[R\left(S, L^{BS}_{(1,s)}\right)\right]_{:,m_{BS}}$

for $m_{MS} \le KT_d$ do

By MS evaluation is done by exploiting $\left[V\left(S, L^{BS}_{(1,s)}\right)\right]_{:,m_{MS}}$

Subsequent to measure MS $x_{m_{BS}} = \sqrt{P_s}\left[V\left(S, L^{BS}_{(1,s)}\right)\right] C\left[R\left(S, L^{BS}_{(1,s)}\right)\right]_{:,m_{BS}} + n_{m_{BS}}$

$x_{(s)} = \left[x^L_1, x^L_2, \; x^L_K\right]^L$

for $p = 1 \le l - 1$ do

$g = R^L_{\left(S, L^{BS}_{(p,s)}\right)} \left[F_{BS,D}\right]^{*}_{:,L^{BS}_{(p,s)}} \otimes W^C_{\left(S, L^{BS}_{(p,s)}\right)} \left[F_{MS,D}\right]_{:,L^{BS}_{(p,s)}}$

$x_{(S)} = x_{(S)} - x^C_{(S)} g \left(g^C g\right) g$

$Y = \text{matix}\left(x_{(S)}\right)$ return $x_{(S)}$ to matrix format

$\max\left[Y_{(S)} \Theta Y^{*}_{(S)}\right]$ -fitness

Update ϖ using proposed **PSO-GSA** model.

end for

end for

end for

5. Proposed Hybrid PSO-GSA Model

5.1 PSO Model

The conventional PSO algorithm [10] is exploited to update the velocity and location of the swarm [13].

$$u_{t+1} = u_t + c_1\varepsilon_1\left[p^* - y_t\right] + c_2\varepsilon_2\left[g^* - y_t\right] \tag{12}$$

whereas c_1 and c_2 indicates the constants referred to as cognitive and social coefficients, p^* and g^* indicates the personnel and global optimal locations, correspondingly; ε_1 and ε_2 indicates the random numbers.

The coefficient of v_t is added as follows:

$$u_{t+1} = wu_t + c_1\varepsilon_1\left[p^* - y_t\right] + c_2\varepsilon_2\left[g^* - y_t\right]$$

The coefficient u_t indicates a fractional number called as an inertia coefficient. In the swarm position by exploiting the velocity formulation, the update is as below:

$$x_{t+1} = x_t + v_{t+1} \tag{13}$$

5.2 GSA Model

In the conventional GSA algorithm, the swarm velocity is updated as below: [11]

$$u_{t+1} = \varepsilon_3 u_t + a_t \tag{14}$$

$a_t = \dfrac{F_t}{M_t}$, indicates the particle acceleration with $M_t = \dfrac{m_t}{\sum m_t}$ being the mass of each particle and possessing $m_t = \dfrac{fit_t - worst_t}{best_t - worst_t}$. The worst indicates the worst fitness, fit indicates the fitness, and best indicates the optimal fitness from all of the particles. The force $F_t = \sum \varepsilon G_t \dfrac{M_1^i M_1^j}{R_{ij}}\left(x_t^i - x_t^j\right)$, whereas R_{ij} indicates the Euclidean distance between the particles, ε indicates the random number, and $G_t = G_0 \exp\left(-\eta \dfrac{iter}{iter_{max}}\right)$ indicates the gravitational constant whose values based on the constants, G_0 and η where, $iter$ and $iter_{max}$ indicates the iteration number as well as an utmost number of iterations, correspondingly.

5.3 Proposed Hybrid PSO-GSA algorithm

The hybrid model of the PSO and the GSA algorithm is stated as

$$u_{t+1} = wu_t + c_1\varepsilon_1 a_t + c_2\varepsilon_2\left[g^* - y_t\right] \tag{15}$$

$$u_{t+1} - wu_t = c_1\varepsilon_1 a_t + c_2\varepsilon_2\left[g^* - y_t\right] \tag{16}$$

By exploiting the inertia coefficient magnitude, $w = 1$. The left-hand side of the aforesaid formulation indicates the discrete form of the derivative. Fractional-order calculus is exploited to expand the left-hand side of the aforesaid formulation is stated as below:

$$\begin{aligned} & u_{t+1} - bv_t - \frac{1}{2!}b(1-b)v_{t-1} - \frac{1}{3!}b(1-b)v_{t-1}(2-b)v_{t-2} \\ & -\frac{1}{4!}b(1-b)v_{t-1}(2-b)v_{t-2}(3-b)v_{t-3} \\ & -\frac{1}{5!}b(1-b)v_{t-1}(2-b)v_{t-2}(3-b)v_{t-3}(4-b)v_{t-4} = c_1\,\varepsilon_1\,a_t + c_2\,\varepsilon_2\left[g^* - x_t\right] \end{aligned} \tag{17}$$

Hence, the velocity update is formulated as below:

$$\begin{aligned} & u_{t+1} = bv_t + \frac{1}{2!}b(1-b)v_{t-1} + \frac{1}{3!}b(1-b)v_{t-1}(2-b)v_{t-2} \\ & +\frac{1}{4!}b(1-b)v_{t-1}(2-b)v_{t-2}(3-b)v_{t-3} \\ & +\frac{1}{5!}b(1-b)v_{t-1}(2-b)v_{t-2}(3-b)v_{t-3}(4-b)v_{t-4} + c_1\,\varepsilon_1\,a_t + c_2\,\varepsilon_2\left[g^* - x_t\right] \end{aligned} \tag{18}$$

Aforesaid formulation states that 4 preceding variables are needed to compute the swarm velocity. It is exploited as an update model for the swarm particles by choosing the magnitude of the fractional coefficient b. To a particular issue, an absolute range from 0 to 1 might be verified, and the value appropriate for superior convergence might be exploited.

6. Result and Discussion

In MATLAB, the developed technique was implemented and the consequent results were attained. Here, the performance of the developed methodwas analyzed over the other existing techniques regarding the performance metrics like Mean Square Error (MSE), and CSI.

The performance analysis of the proposed method regarding MSE and CSI are summarized in Table 1 and Table 2 respectively for varied channel bandwidths of 100 and 500. Subsequently, the analysis is performed by evaluating the proposed technique with the existing optimization such as Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). In reality, the meta-heuristic methods are stochastic in nature. Therefore to obtain accurate outcomes, the methods get executed 5 times and the statistical result is obtained. From Table I, the best value regarding least MSE is attained by the proposed method. While evaluating this outcome value, the conventional techniques exhibit their poor performance with maximized error. For the Best, the proposed method is 16% better than the PSO, and 18% better than the GSA algorithms and for the mean the proposed method is 22% better than the PSO, and 25% better than the GSA algorithms in consideration of channel bandwith= 100. Table II illustrates the performance analysis of the proposed model over the conventional models regarding the CSI. For the Channel bandwidth =100, the proposed method is 24% better than the PSO, and 28% better than the GSA algorithms regarding the best value. Regarding the mean value, the proposed method is10% better than the PSO, and 30% better than the GSA algorithms for the channel bandwidth =100.

Table 1 *Performance Analyis Of Proposed Method Regrding MSE*

Channel bandwidth=100			
Measures	**PSO**	**GSA**	**Proposed**
Best	0.28068	0.25233	0.09225
Worst	0.02393	0.0086	0.00855
Mean	0.06386	0.08593	0.05236
Median	0.04909	0.08089	0.04585
Std-dev	0.06253	0.09881	0.03281
Channel bandwidth=500			
Measures	**PSO**	**GSA**	**Proposed**
Best	0.26605	0.28506	0.22585
Worst	0.02349	0.02349	0.03292
Mean	0.06956	0.08482	0.06887
Median	0.03445	0.0808	0.08334
Std-dev	0.06699	0.06498	0.03536

Table 2 *Performance analyis of proposed method regrding CSI*

Channel bandwidth=100			
Measures	**PSO**	**GSA**	**Proposed**
Best	36.033	34.888	39.836
Worst	9.2699	9.4348	39.06
Mean	29.603	28.04	38.329
Median	26.693	29.362	39.436
Std-dev	6.3669	6.9366	2.3633
Channel bandwidth=500			
Measures	**PSO**	**GSA**	**Proposed**
Best	33.839	34.994	36.98
Worst	8.8906	9.6333	32.203
Mean	26.363	26.303	34.889
Median	23.949	26.263	36.309
Std-dev	6.9933	9.0269	3.3399

7. Conclusion

The pilot overhead provides basic limits on the performance of MIMO systems. This is due to the performance of such systems is on the basis of the failure of the presentation of precise CSI. Based on the theory of compressive sensing, in this work, a minimum complexity channel estimation was performed which performed by encoding and precoding process. A new heuristic method was set up which optimizes the codebook for precoding as well as combining procedure. The developed model was helpful for both imperfect as well as perfect CSI. This method shows the minimum computational complexity. In addition, the developed method named the Hybrid PSO-GSA model was proposed which was the combination of PSO and GSA algorithm correspondingly. Finally, the performance analysis exhibits that the developed method possesses better results than the conventional models.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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