Rank Reduction and Diagonalization of Sensing Matrix for Millimeter Wave Hybrid Precoding Using Particle Swarm Optimization

Mayank Lauwanshi and E. S. Gopi

Abstract Millimeter wave (mmwave) wireless communication systems is a promising technology which provides a high data rate (up to gigabits per second) due to the large bandwidth available at mmwave frequencies. But it is challenging to estimate the channel for mmwave wireless communication systems with hybrid precoding, since the number of radio frequency chains are much smaller as compared to a number of antennas. Due to limited scattering, the Beam space channel model using Dictionary matrices is proposed for mmwave channel model. There were many attempts made to design the precoder and decoder, along with the channel estimation for the mmwave channel model but it remains an unsolved problem. In this paper, we demonstrate the methodology of using Particle Swarm Optimization to design the precoder and decoder of the Beam space channel model with the prior knowledge of Angle of Arrival (AOA) and Angle of Departure (AOD). Particle swarm optimization is used to optimize the precoder and decoder such that the sensing matrix is diagonalized (diagonalization method) and is a reduced rank matrix (rank reduction method) and then the channel matrix is estimated. The results reveal the possible direction to explore the usage of computational intelligence technique in solving the mmwave channel model.

Keywords Computional intelligence · Particle swarm optimization (PSO) · mmwave · Hybrid precoding · Diagonalization · Angle of arrival (AOA) · Angle of departure (AOD)

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1 Introduction

The 5G technology demands 10 Gbps data rate, connecting 1 million devices per square km and 1ms round trip latency, requires 99.9999% availability and reduction in power consumption and improvement in efficiency. One way to achieve this is to use the unused high frequency mmwave band (6–300 GHz). The 57–64 GHz is considered as the oxygen absorption band and 164–200 GHz is considered as the water vapor absorption band. The remaining vast bandwidth of 252 GHz is available in the mmwave band. The Millimetre Wave MIMO technology [1, 2], is more suitable for Backhaul in urban environment in densely distributed small cells. This is also suitable for high data rate, low latency connectivity between vehicles. The conventional Sub 6 GHz MIMO assumes the model $\mathbf{y} = \mathbf{Hx}+\mathbf{n}$, where $\mathbf{H}$ is the channel matrix, $\mathbf{x}$ is the transmitter symbol vector, $\mathbf{y}$ is the received symbol vector and $\mathbf{n}$ is the noise vector. Mostly, all signal processing action takes place in the baseband. There exists a separate RF chain for each antenna. The mmwave wireless propagation has higher propagation losses and reduced scattering. Hence the model adopted for Sub 6 GHz MIMO is not suitable for mmwave MIMO. Beam space channel model is more suitable for Millimeter wave. There were proposals made on the channel estimation and Hybrid precoding.

Digital baseband precoding with a large number of antennas is one of the baseband approaches used for the mmwave communication, where beamforming technique is used to increase spectral efficiency [3–5]. In digital baseband precoding, each antenna is driven with the RF chain and multiple streams of the data are transmitted simultaneously. Due to the large antenna, the energy consumption in the mmwave band is very high and also the hardware for digital precoder is complex and costly due to which it is not a suitable technique for channel estimation and precoding for mmwave. To overcome the above hardware limitation, analog beamforming solutions are proposed in [6–9]. In analog beamforming, the main idea is to vary the phase of the transmitted signal while keeping its magnitude fixed, i.e., analog beamformers are used as phase shifters. The analog beamformers have reduced system complexity because the antennas share only one RF chain. But as antennas share only one RF chain, only a single data stream is transmitted at a time due to which spectrum efficiency gets limited. The digital and analog beamforming techniques are not useful for mmwave communication individually, so the compromise is made between the spectral efficiency and hardware complexity and Hybrid beamforming (HBF) is proposed in which both analog and digital beamformers are used.

In [10], hybrid precoding algorithm was proposed in which phase shifters with quantized phase are required to minimize the mean-squared error of the received signals but the work in this paper does not account for mmwave characteristics. In [11] and [12], the hybrid precoding design problem was proposed such that the channel is partially known at the transmitter in the system. In [13] investigation of the hybrid precoding design is done for fully connected structure-based broadband mmWave multiuser systems with partial availability of Channel state information. Although the algorithms developed in [11–13] supports the transmission of multiple streams and the hardware limitations are also overcome to great extent but they are not as effective as compared to the digital precoding algorithm when it comes to system performance. In [14], hybrid precoding algorithm for mmWave communication system was proposed. In this algorithm, quantized beam steering direction is given importance. Also, multi-resolution codebook is designed for training the precoders and the codebook depends on hybrid (i.e., joint analog and digital) processing to generate different beamwidths beamforming vectors. This algorithm improves the system performance to some extent and also overcomes the hardware limitations but this algorithm is quite complex. So, there is a need to develop a less complex and more effective algorithm for the channel estimation and hybrid precoder and decoder design.

In this chapter, we propose a less complex and effective channel estimation and hybrid precoder and decoder designing algorithm for a mmWave system based on the computational intelligence algorithm, Particle swarm optimization. The main assumptions which we have considered on the mmwave hardware while developing the algorithm are (i) the analog phase shifters have constant magnitude and varying phases, and (ii) the number of RF chains are less than the number of antennas. Using particle swarm optimization, we are optimizing the baseband precoder and decoder such that the sensing matrix is a diagonal matrix (Diagonalization method) and reduced rank matrix (rank reduction method) and hence the channel matrix is estimated.

The rest of the chapter is organized as follows. Section 2 explains the particle swarm optimization algorithm. In Sect. 3, System model, problem formulation, and main assumptions considered in the chapter are discussed. Section 4 presents the methodology to solve the above problem. Here we discuss the pseudo code for the objective functions used in PSO for the diagonalization of the matrices and reduction of rank of the matrix and also the workflow to design the precoder and decoder and hence to estimate channel matrix. Section 5, demonstrates the simulation results obtained after performing the experiments, and finally the paper is concluded.

2 Particle Swarm Optimization

This section discusses the particle swarm optimization algorithm [15] which is used to diagonalize and reduce the rank of the matrix.

To understand PSO, let's consider the behavior of bird flocking. Suppose the birds are searching for the food in a particular area and they do not know about the exact location of the food. But they know how far the food is from them after each iteration. So what should birds do to find the exact location of the food? The effective way is to consider individual decisions along with the decisions taken by the neighbors to find the optimal path to be followed by the birds.

According to the PSO algorithm, Initialization with random particles (solutions) is done first and then optimum is searched by updating generations. In every iteration, each particle is updated by two values, personal best and global best. The personal best (pbest) value is the best solution achieved by the individual particle so far. And the global best (gbest) value is the common experience of all the particles in

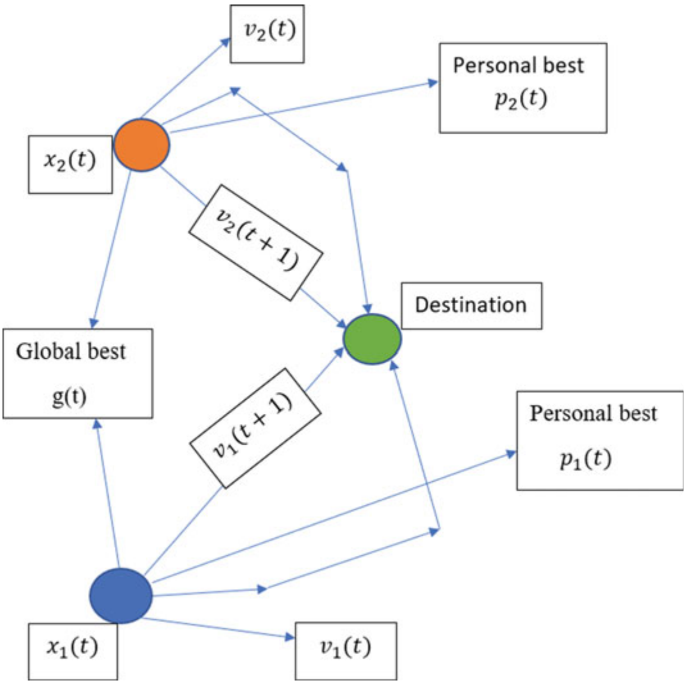

Fig. 1 Position updation of particle using PSO

the population. It is the best value achieved so far by any of the particles in the population.

After finding the personal best and global best, the particle updates their position according to the following equations:

$$\mathbf{next{=}present{+}C1} \times \mathbf{rand} \times \mathbf{(pbest\text{-}present){+}\ C2} \times \mathbf{rand} \times \mathbf{(gbest\text{-}present)} \quad (1)$$

Figure 1 shows how the position of particles ($x_1(t)$ and $x_2(t)$) is updated based on the value of the global best and individual personal best using the PSO algorithm.

3 Problem Formulation

3.1 Millimeter Wave System Model

The block diagram of the millimeter wave wireless communication system is shown in Fig. 2. It consists of baseband precoder and decoder, RF precoder and decoder, and RF chains as main blocks. From the block diagram, the baseband received signal **Y** can be modeled as follows:

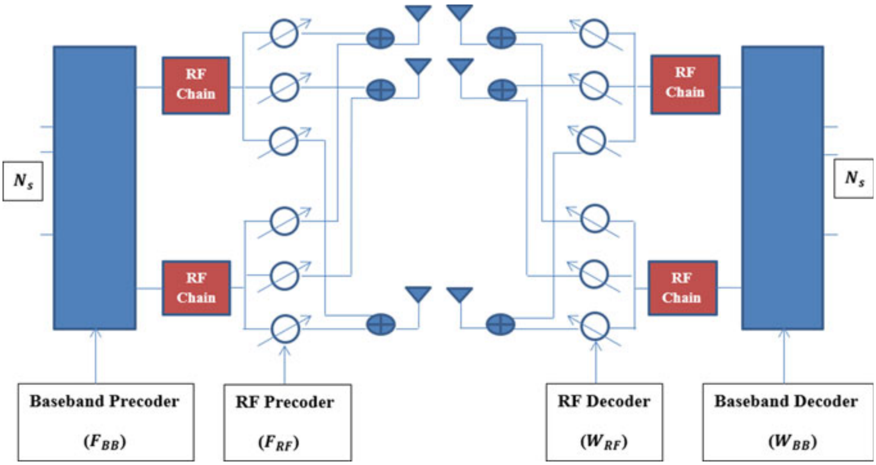

Fig. 2 Illustration of the architecture of millimeter wave transceivers system

$$\mathbf{Y} = \sqrt{(\mathbf{P})}\mathbf{W_{BB}^H W_{RF}^H H F_{RF} F_{BB} X} + \mathbf{N} \tag{2}$$

$$\mathbf{y} = \sqrt{(\mathbf{P})}(\mathbf{W_{BB}^H W_{RF}^H} \otimes \mathbf{F_{BB}^T F_{RF}^T})\mathbf{h} + \mathbf{n} \tag{3}$$

Equation (3) is the vector form of (2) which is obtained by considering input $\mathbf{X}$ as identity matrix. Here $\mathbf{H}$ is the channel matrix and $\mathbf{N}$ is the gaussian noise. $\mathbf{F_{BB}}$ is the baseband precoder and $\mathbf{F_{RF}}$ is the RF precoder. RF precoder is practically realized using phase shifters. Hence the elements of the matrix $\mathbf{F_{RF}}$ are having the magnitude unity. Similarly, $\mathbf{W_{BB}}$ is the baseband decoder and $\mathbf{W_{RF}}$ is the RF decoder. $\mathbf{X}$ (with size $N_s \times 1$) is the symbol vector to be transmitted. $\mathbf{F_{BB}}$ is of the size $N_{RF} \times N_s$. Also the size of the matrix $\mathbf{F_{RF}}$ is $N_t \times N_{RF}$, where N_t is the number of transmitter antennas and N_{RF} is the number of RF blocks. The channel matrix is of size $N_r \times N_t$. The size of the matrix $\mathbf{W_{RF}}^H$ is $N_{RF} \times N_r$ and the size of the matrix $\mathbf{W_{BB}}^H$ is $N_s \times N_{RF}$.

The channel matrix $\mathbf{H}$ can further be modeled as following:

$$\mathbf{H} = \mathbf{A_R H_b A_T^H} \tag{4}$$

where $\mathbf{A_R}$ is the dictionary matrix in the receiver array antenna and $\mathbf{A_T}$ is the dictionary matrix in the transmitter array antenna as given below. The size of the matrices $\mathbf{A_R}$ and $\mathbf{A_T}$ are given as $N_r \times G$ and $N_t \times G$ respectively. In this the angle θ_i^r are the angle of arrivals of the receiving antenna (Mobile station) and θ_i^d are the angle of departures of the transmitting antenna (Base station).

$$\mathbf{A_R} = \begin{pmatrix} 1 & 1 & 1 & \cdots \\ e^{-\frac{j2\pi}{\lambda} d_r cos(\theta_1^r)} & e^{-\frac{j2\pi}{\lambda} d_r cos(\theta_2^r)} & e^{-\frac{j2\pi}{\lambda} d_r cos(\theta_3^r)} & \cdots \\ e^{-\frac{j2\pi}{\lambda} (2d_r) cos(\theta_1^r)} & e^{-\frac{j2\pi}{\lambda} 2d_r cos(\theta_2^r)} & e^{-\frac{j2\pi}{\lambda} 2d_r cos(\theta_3^r)} & \cdots \\ e^{-\frac{j2\pi}{\lambda} (3d_r) cos(\theta_1^r)} & e^{-\frac{j2\pi}{\lambda} 3d_r cos(\theta_2^r)} & e^{-\frac{j2\pi}{\lambda} 3d_r cos(\theta_3^r)} & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ e^{-\frac{j2\pi}{\lambda} (N_r-1) d_r cos(\theta_1^r)} & e^{-\frac{j2\pi}{\lambda} (N_r-1) d_r cos(\theta_2^r)} & e^{-\frac{j2\pi}{\lambda} (N_r-1) d_r cos(\theta_3^r)} & \cdots \end{pmatrix}$$

$$\mathbf{A_T^T} = \begin{pmatrix} 1 & 1 & 1 & \cdots \\ e^{-\frac{j2\pi}{\lambda} d_t cos(\theta_1^t)} & e^{-\frac{j2\pi}{\lambda} d_t cos(\theta_2^t)} & e^{-\frac{j2\pi}{\lambda} d_t cos(\theta_3^t)} & \cdots \\ e^{-\frac{j2\pi}{\lambda} (2d_t) cos(\theta_1^t)} & e^{-\frac{j2\pi}{\lambda} 2d_t cos(\theta_2^t)} & e^{-\frac{j2\pi}{\lambda} 2d_t cos(\theta_3^t)} & \cdots \\ e^{-\frac{j2\pi}{\lambda} (3d_t) cos(\theta_1^t)} & e^{-\frac{j2\pi}{\lambda} 3d_t cos(\theta_2^t)} & e^{-\frac{j2\pi}{\lambda} 3d_t cos(\theta_3^t)} & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ e^{-\frac{j2\pi}{\lambda} (N_t-1) d_t cos(\theta_1^t)} & e^{-\frac{j2\pi}{\lambda} (N_t-1) d_t cos(\theta_2^t)} & e^{-\frac{j2\pi}{\lambda} (N_t-1) d_t cos(\theta_3^t)} & \cdots \end{pmatrix}$$

The matrix $\mathbf{H_b}$ is the matrix with elements filled up with complex numbers (with real and imaginary part as Gaussian distributed) and is describing the multipath channel coefficients. For each path, one particular angle of departure and the corresponding angle of arrival is activated, and hence the matrix $\mathbf{H_b}$ needs to be sparse so that only few paths are active at a time. Substituting (4) in (3), we get the following:

$$\mathbf{y} = \sqrt{(}\mathbf{P})(\mathbf{W_{BB}^H W_{RF}^H A_R} \otimes \mathbf{F_{BB}^T F_{RF}^T A_T^*})\mathbf{h_b} + \mathbf{n} \tag{5}$$

From (5), we conclude that the requirement is to design the precoder and the decoder such that the sensing matrix $[\sqrt{(}\mathbf{P})(\mathbf{W_{BB}^H W_{RF}^H A_R} \otimes \mathbf{F_{BB}^T F_{RF}^T A_T^*})]$ is the diagonal matrix (diagonalization method) and the rank of the sensing matrix is to be minimized (rank reduction method) to estimate the sparse matrix ($\mathbf{H_b}$) and hence channel matrix ($\mathbf{H}$) from (4).

4 Proposed Methodology

4.1 Diagonalization Method

Initially, we start by initializing matrices $\mathbf{F_{RF}}$ and $\mathbf{W_{RF}}$ as a DFT matrix, in which only the phase of each element of the matrix is varied while magnitude is constant (unity) i.e they are acting as a phase shifters only. Matrices $\mathbf{A_R}$ and $\mathbf{A_T}$ are evaluated based on the specific value of θ, d_r and d_t. Matrices $\mathbf{F_{RF}}$, $\mathbf{W_{RF}}$, $\mathbf{A_R}$ and $\mathbf{A_T}$ are considered as fixed matrices based on the above constraints while implementing PSO. Matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ are selected randomly and PSO algorithm is applied. Matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ are updated after every iteration until sensing matrix $[\sqrt{(}\mathbf{P})(\mathbf{W_{BB}^H W_{RF}^H A_R} \otimes \mathbf{F_{BB}^T F_{RF}^T A_T^*})]$ becomes diagonal matrix . Values of matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ for which sensing matrix is the diagonal matrix are considered as the best value for baseband precoder ($\mathbf{F_{BB}}$) and decoder ($\mathbf{W_{BB}}$) matrices. Figure 3

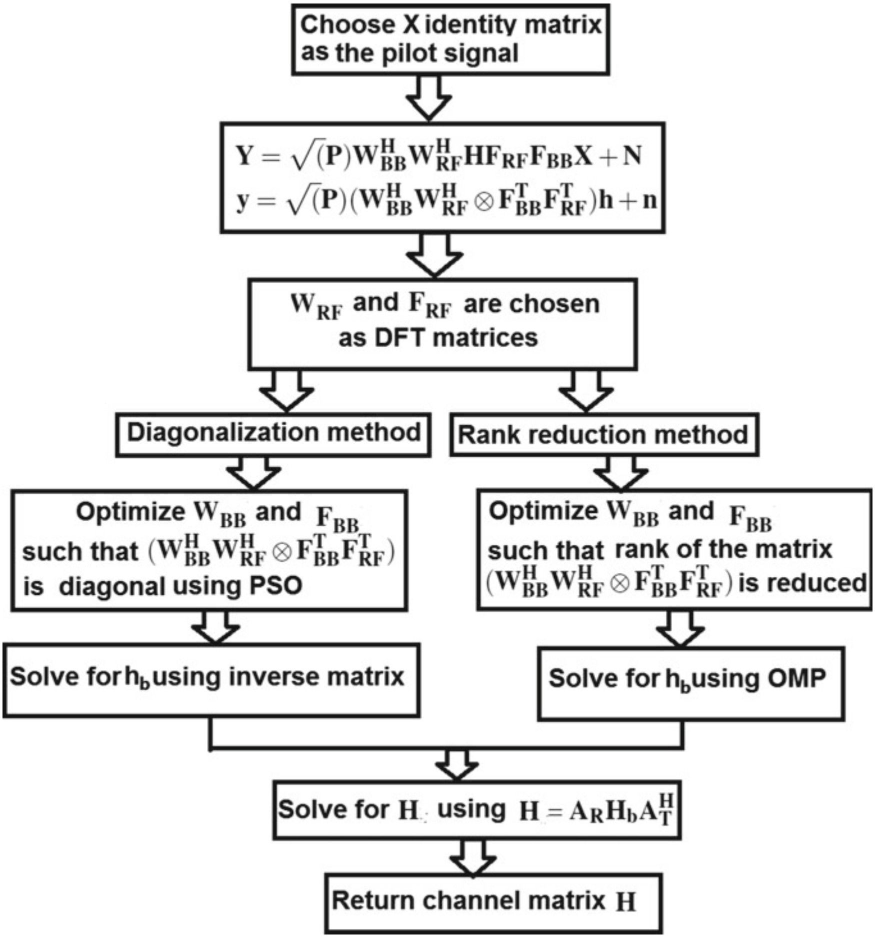

Fig. 3 Flowchart to illustrating the methodology for obtaining channel matrix

shows the flowchart describing the abovediscussed process for the diagonalization of matrix.

Now substitute the obtained diagonalized matrix in the (5). Then take the inverse of the diagonalized matrix and multiple it with 'Y' so as to evaluate matrix $\mathbf{H_b}$ and hence the channel matrix ($\mathbf{H}$) using (1.4).

4.2 *Rank Reduction Method*

In this method, the first four steps are the same as that of diagonalization method. In the fifth step, minimization of the rank of the sensing matrix is done using PSO and corresponding values of matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ are selected for which rank of the sensing matrix is minimized. Now, from this reduced rank sensing matrix, sparse matrix ($\mathbf{H_b}$) is recovered using orthogonal matching pursuit algorithm (OMP). The steps involved in the OMP algorithm are as follows:

- Consider the equation, $\mathbf{y} = \phi\mathbf{h_b}$, where ϕ is the sensing matrix.
- Now, the column of ϕ that has the largest correlation or projection with "y" is estimated.
- Then the best vector $\mathbf{h_b}$ is estimated using the maximum projection column estimated in the above step such that the least square norm is minimized.
- Then the residue or error is estimated and "y" is updated with the value of residue and is used in the next iteration.
- Above process is repeated until the stopping criterion is achieved.

Finally, from the estimated sparse matrix($\mathbf{H_b}$), channel matrix(H) is estimated using (4). Figure 3 shows the flowchart describing the abovediscussed process for the reduction of rank of a matrix.

4.3 Pseudo Code

This section explains the algorithm which we have followed to get the desired output (diagonalized matrix and reduced rank matrix).

Algorithm 1 Algorithm for diagonalization of matrix

Input: $\mathbf{F_{RF}}$, $\mathbf{W_{RF}}$, $\mathbf{A_R}$, $\mathbf{A_T}$ and $\mathbf{X}$;
Randomly generate the initial population for $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$ for 'M' times;
for iteration= 1:N
for i= 1:M
Update the value of $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$ using equation 1 for PSO;
($\mathbf{F_{BB}}new(i)$, $\mathbf{W_{BB}}new(i)$) ;
Update the cost function value;
Update the initial value of matrix $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$;
$\mathbf{F_{BB}}initial(i) = F_{BB}new(i)$;
$\mathbf{W_{BB}}initial(i) = W_{BB}new(i)$;
end for
end for
Cost function;
residual ($\mathbf{F_{BB}}$, $\mathbf{W_{BB}}$)
temp1=$\mathbf{W_{BB}} \times \mathbf{W_{RF}} \times \mathbf{A_R}$;
temp2=$\mathbf{F_{BB}} \times \mathbf{F_{RF}} \times \mathbf{A_T}$;;
res=$\mathbf{kron}(\mathbf{temp1}, \mathbf{temp2})$;
res1=matrix having only diagonal elements of 'res', rest of the elements are made zero;
res2= res;
res=ratio of absolute sum of elements of (res1) to (res2);
Output: Diagonalized matrix

Algorithm 2 Algorithm for rank reduction

Input: $\mathbf{F_{RF}}$, $\mathbf{W_{RF}}$, $\mathbf{A_R}$, $\mathbf{A_T}$ and $\mathbf{X}$;
Randomly generate the initial population for $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$ for 'M' times;
for iteration= 1:N
for i= 1:M
Update the value of $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$ using equation 1 for PSO;
$(\mathbf{F_{BB}}new(i), \mathbf{W_{BB}}new(i))$;
Update the cost function value;
Update the initial value of matrix $\mathbf{F_{BB}}$ and $\mathbf{W_{BB}}$;
$\mathbf{F_{BB}}initial(i) = F_{BB}new(i)$;
$\mathbf{W_{BB}}initial(i) = W_{BB}new(i)$;
end for
end for
Cost function;
residual ($\mathbf{F_{BB}}$, $\mathbf{W_{BB}}$)
temp1=$\mathbf{W_{BB}} \times \mathbf{W_{RF}} \times \mathbf{A_R}$;
temp2=$\mathbf{F_{BB}} \times \mathbf{F_{RF}} \times \mathbf{A_T}$;;
res=$\mathbf{kron(temp1, temp2)}$;
res1=Linear combination of the rows or column of res;
res2= Absolute sum of res1;
Output: Reduced rank matrix

5 Experiment and Results

In this section, the simulation experiments are performed to demonstrate the proposed techniques (A) Diagonalization method and (B) Rank reduction method.

5.1 Diagonalization Method

RF precoder ($\mathbf{F_{RF}}$) and decoder ($\mathbf{W_{RF}}$) matrices are initialized as a DFT matrix, in which only the phase of each element of the matrix is changing while magnitude is constant (unity), i.e., they are acting as a phase shifters only. Dimensions of matrices ($\mathbf{F_{RF}}$) and ($\mathbf{W_{RF}}$) are considered as 32×6 and 64×6, respectively. Input $\mathbf{X}$ is taken as a identity matrix with dimensions 4×4. Dictionary matrices $\mathbf{A_R}$ and $\mathbf{A_T}$ are evaluated based on the specific value of angle of departure ($\theta^{\mathbf{t}}$), angle of arrival ($\theta^{\mathbf{r}}$), spacing between antennas at receiver (d_r) and spacing between antennas at transmitter (d_t). While evaluating dictionary matrices resolution is taken as "4", i.e., only "4" different values of $\theta^{\mathbf{t}}$ and $\theta^{\mathbf{r}}$ are considered. Dimensions of $\mathbf{A_R}$ and $\mathbf{A_T}$ are taken as 64×4 and 32×4. Matrices $\mathbf{F_{RF}}$, $\mathbf{W_{RF}}$, $\mathbf{A_R}$ and $\mathbf{A_T}$ are considered as fixed matrices based on the above constraints while implementing PSO. Now the baseband decoder

Table 1 Simulation prameters

Parameters	Name	Dimension	Range
θ^t	Angle of Departure	–	0-π
θ^r	Angle of arrival	–	0-π
H	Channel Matrix	64×32	–
H_b	Sparse matrix	4×4	–
W_{BB}	Baseband Decoder	6×4	–
F_{BB}	Baseband Precoder	6×4	–
W_{RF}	RF Decoder	64×6	–
F_{RF}	RF Precoder	32×6	–
A_R	Dictionary Matrix	64×4	–
A_T	Dictionary Matrix	32×4	–

($\mathbf{W_{BB}}$) and precoder ($\mathbf{F_{BB}}$) matrices are selected randomly with dimensions 6×4 and 6×4 respectively and PSO algorithm is applied. Matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ are updated after every iteration until matrix $\sqrt{(}\mathbf{P})(\mathbf{W_{BB}^H W_{RF}^H A_R} \otimes \mathbf{F_{BB}^T F_{RF}^T A_T^*})$ becomes diagonal matrix. Table 1 shows the simulation parameters which are considered while performing the experiment.

Now the obtained diagonalized matrix is substituted in (5) and its inverse is evaluated. Then it is multiplied by Y, so that sparse matrix $\mathbf{H_b}$ is evaluated and hence channel matrix $\mathbf{H}$ from (4).

After performing the experiment the obtained results are as follows:

Figure 4 shows the convergence of the PSO algorithm, it shows the minimization of the best cost as the number of iteration is increasing. Figure 5a and b shows the diagonal sensing matrix which we get after applying the PSO algorithm. In this, the diagonal elements (non-zero elements) are represented by the brighter color and the off diagonal element (approximately zero values) are represented by the darker color. Figure 5c and d shows the matrix $\mathbf{H_b}$ which is a sparse matrix, in which only a few elements are non-zero and the rest of the elements are nearly zero. Figure 5e and f shows the magnitude and phase of the 64*32 channel matrix ($\mathbf{H}$). Both magnitude and phase are varying for different elements of the matrix. Figure 6a and b shows the magnitude and phase of the baseband combiner matrix ($\mathbf{W_{BB}}$). Figure 6c and d shows that the magnitude of each element of RF Combiner matrix ($\mathbf{W_{RF}}$) is unity and only phase is changing. Figure 6e and f shows the magnitude and phase of the baseband precoder matrix($\mathbf{F_{BB}}$). Figure 6g and h shows that the magnitude of elements of RF Precoder matrix ($\mathbf{F_{RF}}$) is unity and only phase is changing.

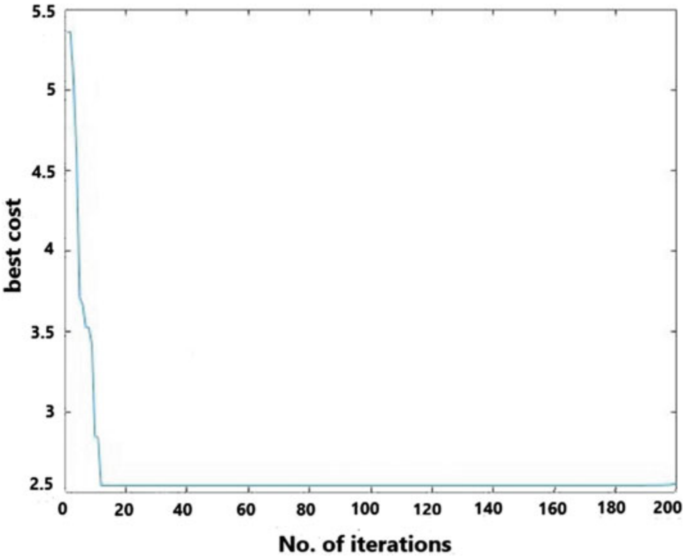

Fig. 4 Convergence of PSO Algorithm for diagonalization of matrix

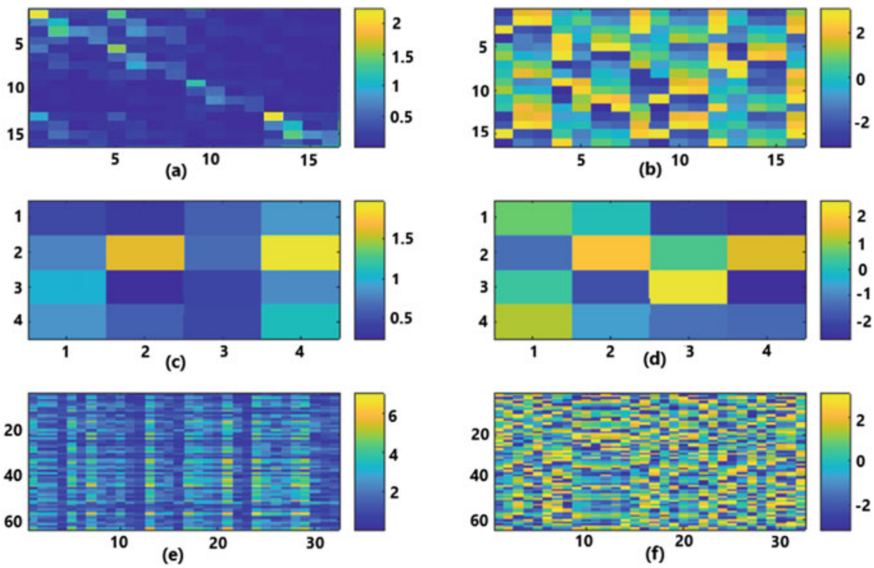

Fig. 5 Illustration of matrices in the form of images, Diagonal sensing matrix obtained using PSO **a** magnitude and **b** phase, sparse matrix (H_b) **c** magnitude and **d** phase, channel matrix (H) **e** magnitude and **f** phase

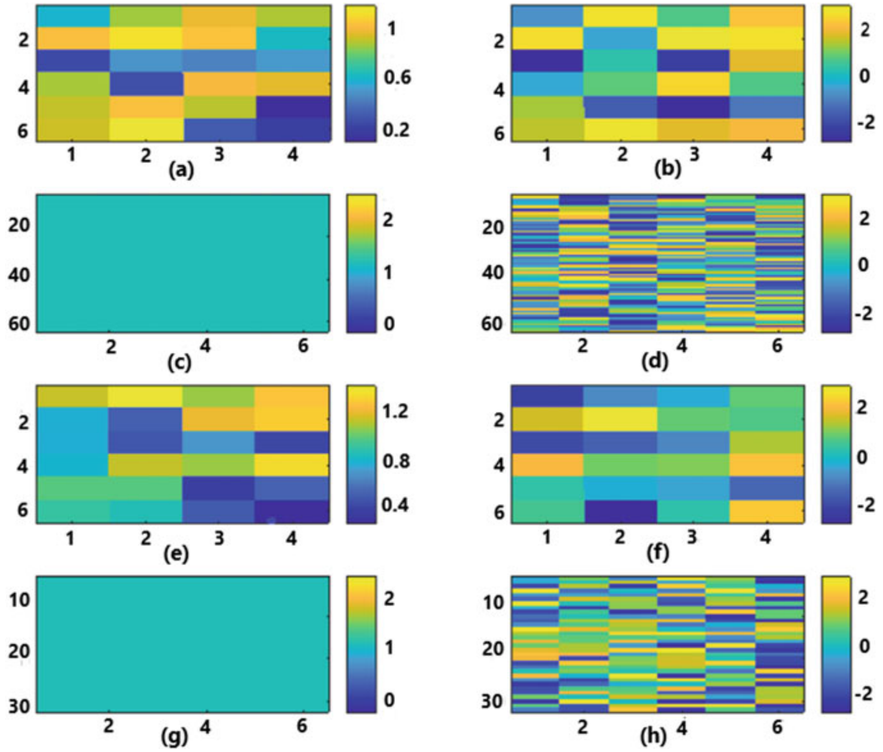

Fig. 6 Illustration of matrices in the form of images, Baseband decoder matrix (W_{BB}) **a** magnitude and **b** phase, RF decoder matrix (W_{RF}) **c** magnitude and **d** phase, baseband precoder matrix (F_{BB}) **e** magnitude and **f** phase, RF precoder matrix (F_{RF}) **g** magnitude and **h** phase

5.2 *Rank Reduction Method*

Initial steps in this method are the same as that of the diagonalization method but the dimensions of some of the matrices are changed here. The dimension for sparse matrix is changed to 16×16, and the dimension of the dictionary matrices $\mathbf{A_R}$ and $\mathbf{A_T}$ are changed to 64×16 and 32×16 respectively. Now, same as in previous method, matrices $\mathbf{F_{RF}}$, $\mathbf{W_{RF}}$, $\mathbf{A_R}$ and $\mathbf{A_T}$ are considered as fixed matrices and the baseband decoder ($\mathbf{W_{BB}}$) and precoder ($\mathbf{F_{BB}}$) matrices are selected randomly with dimensions 6×4 and 6×4 respectively while implementing PSO. Now matrices $\mathbf{W_{BB}}$ and $\mathbf{F_{BB}}$ are updated after every iteration until the rank of the matrix $\sqrt{(\mathbf{P})}(\mathbf{W_{BB}^H W_{RF}^H A_R} \otimes \mathbf{F_{BB}^T F_{RF}^T A_T^*})$ is minimized. Then the matrix $\mathbf{H_b}$ is estimated using the OMP algorithm as explained in the Sect. 4.2 and hence the channel matrix (H) is estimated using (4). Results obtained from this experiment are as follows:

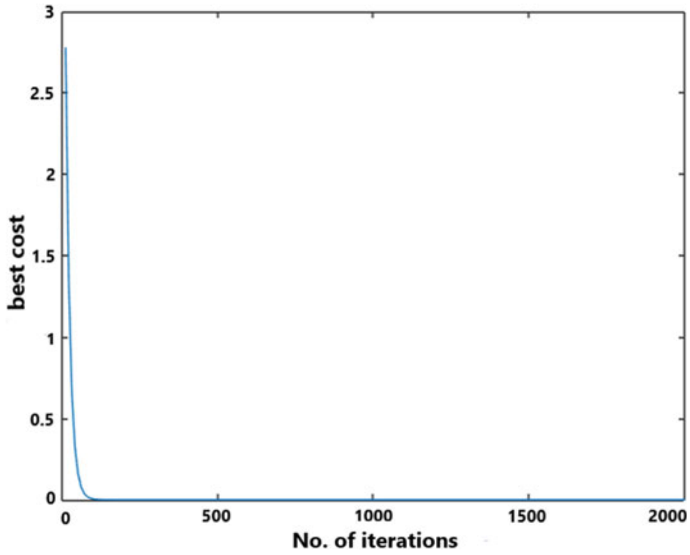

Fig. 7 Convergence of PSO Algorithm for minimization of rank of matrix

Figure 7 shows the convergence of the PSO algorithm for the minimization of the rank of matrix, it shows the minimization of the best cost as the number of iteration is increasing. Figure 8a and b shows the initial sensing matrix with rank 16 before applying the PSO algorithm. Figure 8c and d shows reduced rank sensing matrix with rank 3 obtained using PSO. Figure 8e and f shows the comparison of the sparse matrix ($\mathbf{H_b}$) obtained from both the methods and from the figure it is clear that the matrix obtained from the rank reduction method is of higher order and is more sparse as compared to the matrix obtained from the diagonalization method. So we can say that the rank reduction method is better than diagonalization method for estimating sparse matrix(H_b). Figure 8g and h shows the magnitude and phase of the 64*32 channel matrix ($\mathbf{H}$). Both magnitude and phase are varying for different elements of the matrix. Figure 9a and b shows the magnitude and phase of the baseband combiner matrix ($\mathbf{W_{BB}}$). Figure 9c and d shows that the magnitude of each element of RF Combiner matrix ($\mathbf{W_{RF}}$) is unity and only phase is changing. Figure 9e and f shows the magnitude and phase of the baseband precoder matrix($\mathbf{F_{BB}}$). Figure 9g and h shows that the magnitude of elements of RF Precoder matrix ($\mathbf{F_{RF}}$) is unity and only phase is changing.

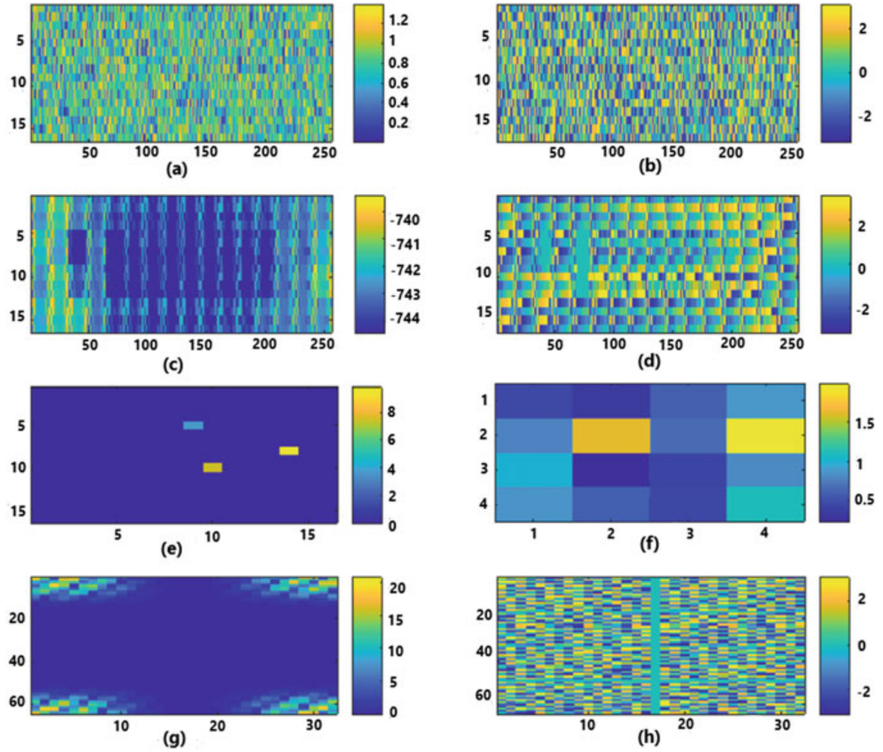

Fig. 8 Illustration of matrices in the form of images, Initial sensing matrix **a** magnitude and **b** phase, reduced rank sensing matrix obtained using PSO **c** magnitude and **d** phase, sparse matrix (H_b) **e** obtained from rank reduction method and **f** obtained from diagonalization method, channel matrix (H) **g** magnitude and **h** phase

6 Conclusion

This chapter demonstrates the proposed methodology to design precoder and decoder for a given pilot signal x and corresponding y by rank reduction and diagonalization of sensing matrix using particle swarm optimization. This helps to estimate the sparse matrix $\mathbf{H_b}$ and hence channel matrix $\mathbf{H}$. The precoder and decoder are designed by considering large number of transmitter and receiver antennas (typically for N_t=32 and N_r=64). The results are obtained with high accuracy and speed, for a large number of transmitter and receiver antennas. The rank reduction method is considered as more suitable as compared to the diagonalization method on the basis of the sparse matrix $\mathbf{H_b}$ estimated in both the methods. The complexity of the above proposed methodology increases if the number of transmitter and receiver antennas are increased further. So for the future work, it would be interesting to explore other constraint optimization techniques to overcome the above problem.

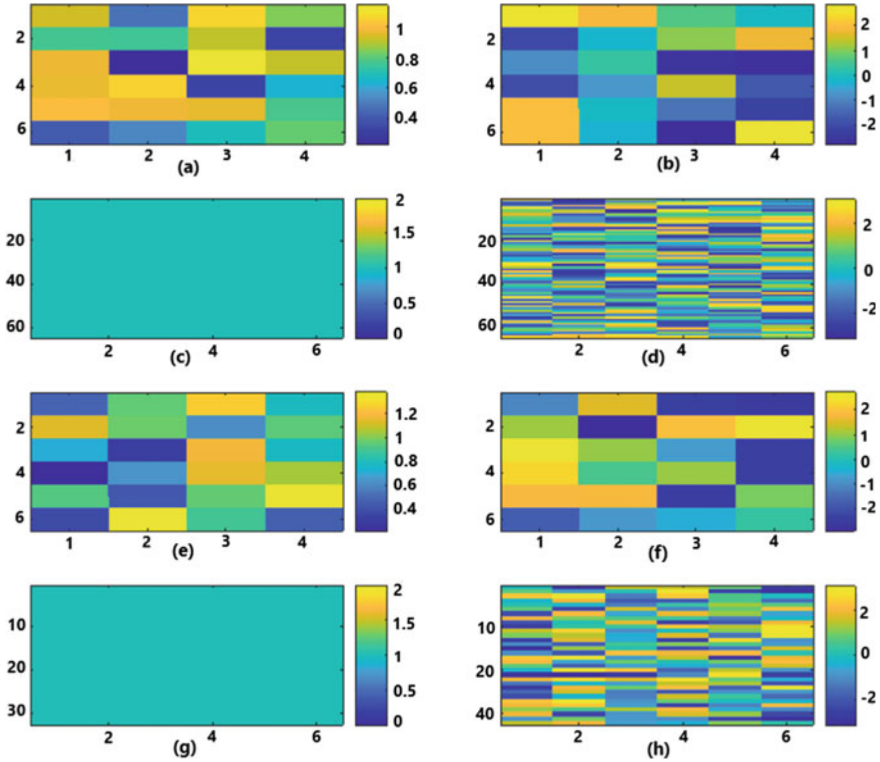

Fig. 9 Illustration of matrices in the form of images, Baseband decoder matrix (W_{BB}) **a** magnitude and **b** phase, RF decoder matrix (W_{RF}) **c** magnitude and **d**, baseband precoder matrix (F_{BB}) **e** magnitude and **f** phase, RF precoder matrix (F_{RF}) **g** magnitude and **h** phase phase

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