Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

AI based Computation for Hybrid Precoding/Combining in Millimeter-Wave Massive MIMO Systems

To cite this article: Nazeerunnisa and Madhavi Tatineni 2021 *J. Phys.: Conf. Ser.* **1817** 012013

AI based Computation for Hybrid Precoding/Combining in Millimeter-Wave Massive MIMO Systems

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Abstract: Millimeter-wave (mm-Wave) have emerged as a potential leading technology for the 5G cellular systems due to the enormous availability of high radio-frequency spectrum, which can deliver extreme data speed and enhance spectral efficiency (SE). An economical architecture of hybrid precoder (HP) is widely used in mm-Wave massive MIMO systems (mm-WmM) to recompense for the severe propagation loss of the mm-Waves. This paper examines the design of the hybrid precoder and combiner (HPC) in mm-WmM by integrating Artificial Intelligence (AI) based optimization algorithm. AI is going to be a key component to enhance the performance of 5G wireless communications and beyond. The emerging AI based computation using Hierarchical Particle Swarm Optimization technique (HPSO) is proposed to design a HPC to maximize the SE in mm-Wave massive MIMO systems. Results obtained from simulations demonstrate the improved performance of the HPSO algorithm in contrast to the existing algorithms and can accomplish close to the optimal performance.

Index Terms – Hybrid precoding/combining, mm-Wave, SNR; Spectral efficiency, PSO

1. Introduction

Every new generation of cellular system takes a significant step towards higher capabilities compared to existing ones. The mm-Wave communication with very high speeds and low latency makes it a suitable and an eminent candidate for 5G cellular systems [1]-[4]. In mm-Wave massive MIMO systems achieving high-quality communication requires the use of large antenna arrays at both the base station and mobile stations [5]. One of the important problems for mm-Wave communications is the huge direction and penetration losses at these frequencies. Beamforming compensates for any signal loss by switching automatically to the strongest beam, and the switching of the beam is done instantaneously to achieve a wide coverage using mm-Wave spectrum. Many industries are committed to improve the speed and connectivity in 5G cellular mobiles to meet the drastic growth in the traffic [6]. Recently, mm-Wave with a spectrum of 30GHz to 300GHz has gained huge attention as a prominent part of 5G and may also to be an integral part of future generation 6G as well. The mm-Waves and also sub-mm-Waves or TeraHertz waves that are 1/10th of the mm-Waves are in enormous research by the industries around the globe.

Nevertheless, because of atmospheric attenuation, rain, poor penetration, mm-Wave signals confront extreme propagation loss compared to current sub-6GHz cellular bands [6]. Vast antennas are placed in the same physical dimension due to the short wavelength of mm-Wave. Massive antenna arrays provide beam-forming gains to get over the path loss due to propagation and synthesize highly directional beams. It also allows multiple data streams to be transmitted simultaneously leading to significant improvement in SE.

Full-digital precoding (DP) is performed in the conventional MIMO systems, which can monitor the signal's magnitudes and phases. However, a committed Radio Frequency (RF) chain is needed for each antenna component that makes it unfeasible, very expensive and it consumes high energy. To tackle the above problem, HP architecture is proposed, where hardly fewer RF chains is needed between a low-dimensional DP and a high-dimensional AP [7] [8]. HP is given attention in mm-WmM to improve system performance [9][10]. The earlier work on HP technology conveys that optimization of SE can be achieved by reducing the euclidean distance between HP and a conventional full-DP [11]. This process makes the HP layout a question of matrix factorization, which is difficult to solve due to constraints in analog hardware device. Using the sparse scattering characteristics of mm-Wave streams, HP model based on the codebook is studied and the corresponding analog parts are chosen from predefined dictionaries such as discrete Fourier transform beam formers [5], [12], [13]. An Orthogonal matching pursuit (OMP) algorithm, offers good quality HPC are proposed in papers [1]-[5],[18]. Further to reduce the OMP algorithm's complexity, a partially modified algorithm was suggested [14] [15]. The AP was designed by implementing the interior-point method in [16]. The author transforms the optimization problem in to a simple form using Coordinate Descent Method (CDM) algorithm and then extracts the closed-form expression to construct AP [17].

Two alternating algorithms are proposed in [19], the first is an alternative minimization algorithm based on Manifold optimization (MO-AltMin) and second one is the Phase Extraction AltMin (PE-AltMin) algorithm. Nonetheless, the number of unit modulo constraints can be considerably large due to the large antenna range involving high computation complexity for the MO-AltMin whereas its lesser for PE-AltMin , but it also causes some performance loss. The AP and combiner are implemented by iterative phase matching algorithm using phase shifters with low resolution [21], [23]. A codebook-based joint HP and a multi-stream combiner model for mm-WmM is proposed in [20]. The Gram-Schmidt orthogonalization also suggests a HP algorithm for a wideband mm-Wave system with minimal channel feedback. A heuristic algorithm for designing single-user and multi-user mm-Wave systems with hybrid precoder is proposed in [22], [24].

AI has created a tremendous impact and value in different industries, it is difficult to think of an industry without AI in upcoming years from now. PSO is an intelligent evolutionary computation and a stochastic optimization algorithm inspired by nature, based on swarm intelligence, such as a shoal of fish, a flock of birds etc. to find food (Maximization) or to risk of predators (Minimization), by dividing in to groups. Hierarchical Particle Swarm Optimization technique (HPSO) is proposed for precoding design to obtain the optimal precoding vector for maximizing the SE in mm-Wave massive MIMO system. In general, rather than reducing the Euclidean distance between the HP and the optimal DP, the HP can be modelled by explicitly optimizing SE to achieve close to optimal performance. Thus HPSO algorithm for HP is proposed for the development of AP and DP, both in narrowband and wideband mm-Wave systems.

Here main contributions are: A hierarchical approach is followed where the HP optimization problem is divided in to analog RF precoder and digital baseband precoder and the optimal AP is modelled using this strategy. Then the optimal AP is set, and the optimal DP is evaluated to improve the SE. Optimization problem of the AP is partitioned in to a sequence of sub-problems and then for each sub problem its closed-form solution is derived. The results portrays that the proposed HPSO algorithm in mm-Wave MIMO system can achieve very close to optimal DP performance with the low computation complexity.

In this paper, section2 includes the process, channel model and the problem formulation, the section3 explores the proposed HPSO algorithm for HPC in mm-WmM, section4 holds the simulation results and finally the section5 reveals the conclusion and future scope of the work.

2. System Representation

A mm-Wave massive MIMO HPC transmission system model with a fully connected structure of a single-user network is as shown in Figure.1. Here N_{T_X} represents the number of transmitting antennas, L_t, L_r represents the number of RF chains at the precoder, combiner respectively ($L_t = L_r = N_{RF}$), N_s represents the incoming data stream, N_{R_X} represents the number of receiving antennas, T_X/ R_X represents the transmitter/receiver, F_B represents the digital baseband precoder, F_R represents the analog RF precoder , W_R represents the analog RF combiner and W_B represents the digital baseband combiner at the R_X. To relay the N_s , they are subject to the constraints that Ns $\leq N_{RF} \leq N_{T_X}$. Assume that $L_t = L_r = N_s$ to support a multi-stream transmission and to minimize the mm-Wave MIMO system's energy cost. The incoming symbols are processed using $L_t \; X \; N_s$ digital baseband precoder F_B and translated via L_t to the RF domain. Then $N_{T_X} \; X \; L_t$, F_R using phase shifters (PSs) precodes these symbols, and sends these data streams through N_{T_X} .

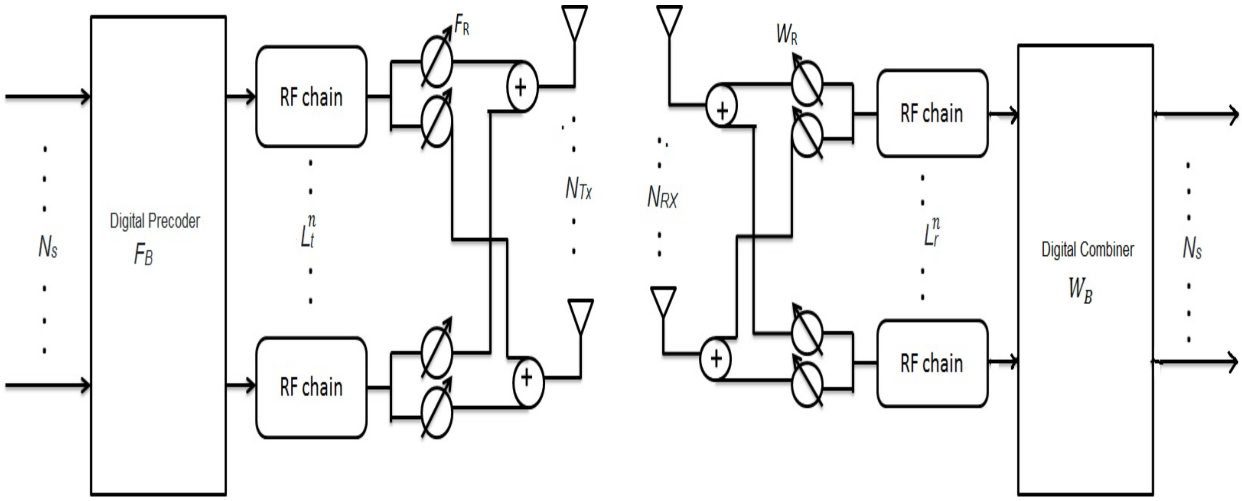

Figure 1: A HPC fully connected structure in mm-Wave MIMO system

The N_{T_X} processes the signal given by (1)

$$x = F_R \, F_B s \tag{1}$$

Where s is the N_s X 1 symbol vector such that $\mathbb{E}[ss^H] = \frac{1}{N_s} \mathrm{I} \, N_s$ Therefore, the DP allows for both amplitude and phase changes. A group of variable PSs are used to implement the analog RF precoder F_R whose components have a constant amplitude constraint $\left|F_{R(a,b)}\right| = 1$ and the transmit power is $\|F_B F_R\|_F^2 = N_s$.

An expanded Saleh-Valenzuela channel model for narrowband mm-Wave system is considered, the signal received at the R_X is given by (2)

$$\bar{y} = \sqrt{\rho} H F_R F_B s + wn \tag{2}$$

Where $\bar{y}$ is the $N_s\ X\ 1$ received vector, ρ is the average received power, H is the $N_{R_X} \times N_{T_X}$ channel matrix, wn is an AWGN noise vector of independent and identically distributed (i.i.d) with $\epsilon\ \mathcal{N}(0, \sigma_{wn}^2)$ mean=0 and variance σ_{wn}^2 , such that $\mathbb{E}[\|H\|_F^2] = N_{T_X} N_{R_X}$.

Assume that both the T_X and R_X has complete information of the channel state information (CSI) of H. At the R_X, a $L_r X\ N_{R_X}$, W_R and $N_s\ X\ L_r$, W_B combiners processes the received signal. So, the received signal after combining is given as (3)

$$\bar{y} = \sqrt{\rho} W_B^H W_R^H H F_R F_B s + W_B^H W_R^H n \quad (3)$$

Just like F_R, the W_R is also implemented with PSs and meets the unit modulo constraints, i.e. $|W_{R(a,b)}| = 1$. The Gaussian signal is processed through the mm-Wave channel, results in SE given in (4)

$$R = \log_2 \det\left(\mathrm{I}_{N_s} + \frac{\rho}{N_s} R_n^{-1}\, W_B^H W_R^H H F_R F_B\ X\ F_B^H F_R^H H^H W_R W_{BB}\right) \quad (4)$$

Where $R_{wn} = \sigma_{wn}^2 W_B^H W_R^H W_R W_B$ is the noise covariance matrix after combining. The HPC for a mm-Wave MIMO systems are modelled jointly to optimize SE. Considering hardware constraint, the corresponding problem can be written as (5)

$$\underset{F_B, F_R, W_R, W_B}{\arg max} \quad R \quad s.t \begin{cases} \|F_R F_B\|_F^2 = N_S, \\ |F_{R(a,b)}| = 1, \quad \forall a, b \\ |W_{R(a,b)}| = 1, \quad \forall a, b \end{cases} \quad (5)$$

This problem of optimization is a combined optimization of the HPC. Due to the non-convex restriction on F_R and W_R , however , it is challenging to solve. The objective function is simplified further to yield satisfactory results in the upcoming sections.

2.1. Millimeter Wave Channel model

An expanded Saleh-Valenzuela channel model based on a narrowband clustered mm-Wave system is used. It is believed that the matrix channel H has S_{clu}scattering clusters, each of which includes P_{path}propagation paths. It is therefore possible to write channel H given in equation (6)

$$H = \eta \sum_{a=1}^{S_{clu}} \sum_{l=1}^{P_{path}} C\mathcal{G}_{al} \alpha_r(\emptyset_{al}^r, \theta_{al}^r)\ \alpha_t(\emptyset_{al}^t, \theta_{al}^t)^H \quad (6)$$

Where η is a normalization factor such as $\eta = \sqrt{\frac{N_{T_X} N_{R_X}}{S_{clu} P_{path}}}$, $C\mathcal{G}_{al}$ is the complex gain of the l-th ray in the a-th scattering cluster. Furthermore $\alpha_r(\emptyset_{al}^r, \theta_{al}^r)\ and\ \alpha_t(\emptyset_{al}^t, \theta_{al}^t)^H$ are the array response vectors at the R_X and T_X, where $\emptyset_{al}^r(\theta_{al}^r)$ and $\emptyset_{al}^t(\theta_{al}^t)$ stand for azimuth and elevation angles of arrivals and angle of departures (AoAs and AoDs), respectively.
For uniform planar array (UPA) in the $yz - plane^2$ with W and H elements on the y and z axes respectively, the array response vectors are expressed by (7)

$$upa_{array}(\emptyset, \theta) = \frac{1}{\sqrt{N}}[\,1, \ldots, e^{jkd(m \sin(\emptyset)\sin(\theta) + n\cos(\theta))}, \ldots, e^{jkd((W-1)\sin(\emptyset)\sin(\theta) + (H-1)\cos(\theta))}]^T \quad (7)$$

Where d is the antenna spacing, $k = \frac{2\pi}{\lambda}$ and λ is the signal wavelength, and $0 \le m \le W$ and $0 \le \frac{\lambda}{n} \le W$ indices in 2D plane and antenna array size is N=WH.

3. Hierarchical Particle Swarm Optimization for HP

Initially the design of the HP is considered and then the proposed HPSO algorithm is implemented to obtain the optimal AP and DP. Since the HPC have similar architecture and computation formulation, the same algorithm can be used to design the hybrid combiner.

3.1. Hybrid Precoder (HP) Design

Here the main aim is to intend a HP design to optimize the transceiver's SE in (5). Nonetheless, this issue in HPC involves joint optimization, which is difficult to solve. To simplify the design of the transceiver, the problem of joint $T_X - R_X$ optimization is temporarily decoupled and HP model is considered in (8) as

$$\underset{F_R,\ F_B}{arg\max}\, log_2 \det\left(\mathrm{I} + \frac{\rho}{N_s\sigma_{wn}^2} H F_R F_B F_B^H F_R^H H^H\right) \tag{8}$$

$$s.t\begin{cases}\|F_R F_B\|_F^2 = N_s & \forall a,b \\ F_R(a,b) = 1, & \forall a,b\end{cases}$$

Clearly, due to F_R's unit modulo constraint, it is intractable to jointly optimize F_B and F_R. A centralized approach for developing DP and AP is followed inspired by [22]. The water-filling method is used in the first part to design the optimal F_B, assuming that AP is fixed. In the second part, focus is on AP design based on the optimized DP F_B . The F_R optimization problem is decimated into a series of sub-problems and the HPSO algorithm is used to design each component of F_R until convergence.

3.2. Digital Precoder (DP) Design

Assume that AP is fixed, consider the DP design to enhance the SE. Further simplifying HP design and decouple the DP and AP in the power constraint, and set $F_B = \sqrt{(F_R^H F_R)}\,\tilde{F}_B$ where $\tilde{F}_B$ is a dummy variable, and then bring F_B in to (8), hence the DP design problem can be rewritten as(9)

$$\underset{\tilde{F}_B}{arg\max}\, log_2 \det\left(\mathrm{I} + \frac{\rho}{N_s\sigma_{wn}^2} H_{eff}\tilde{F}_B\tilde{F}_B^H {H_{eff}}^H\right) \tag{9}$$

$$s.t.\ \left\|\tilde{F}_B\right\|_F^2 = N_s$$

Where $H_{eff} = HF_R\left(\sqrt{F_R^H F_R}\,\right)$ is an effective channel, the objective function in (9) has only one $\tilde{F}_B$ as the optimization variable. The corresponding solution of $\tilde{F}_B$ is given as (10)

$$\tilde{F}_B = S_{vec}F_{diag} \tag{10}$$

Where S_{vec} represents first S_n column of right singular vectors of H_{eff}. F_{diag} is a diagonal matrix, whose elements are water-filling power control solution. The optimal solution is found given by (11)

$$F_B = \sqrt{F_R^H F_R}\,\tilde{F}_B = \sqrt{F_R^H F_R} S_{vec}F_{diag} \tag{11}$$

3.3. Analog precoder (AP) design

Here the focus is on the AP design to optimize SE, for the optimal digital precoder. It was shown in [22] that the AP is highly likely to satisfy $F_R^H F_R \propto \mathrm{I}$ when the number of antennas appears to be infinite, obtains (12)

$$F_B = \sqrt{F_R^H F_R} S_{vec} F_{diag} \approx S_{vec} F_{diag} \tag{12}$$

S_{vec} is also a unit matrix if $L_t = L_r = N_s,\ F_{diag} \approx \gamma\, \mathrm{I}$ where γ is factor of normalization , assume that all N_s have equal power allocation, obtains $F_B F_B^H = \gamma^2\, \mathrm{I}$. Rewriting the problem of optimization in (8), obtains (13)

$$\begin{aligned} &\underset{F_R}{arg\max}\, log_2 \det\left(\mathrm{I} + \frac{\rho\gamma^2}{N_s \sigma_{wn}^2} H F_R F_R^H H^H\right) \\ &s.t.\quad |F_R(a,b)| = 1,\ \forall\, a, b \end{aligned} \tag{13}$$

Since the F_R column permutation does not change the result of $F_R F_R^H$, it is possible to rewrite $F_R F_R^H$ as in (14)

$$F_R F_R^H = [(F_R)_{-b} f_b][(F_R)_{-b} f_b]^H \tag{14}$$

Where $(F_R)_{-b}$ is a sub matrix of F_R excluding the b-th column f_b. The auxiliary matrix AU_b in (15)

$$AU_b = \mathrm{I} + \frac{\rho\gamma^2}{N_s \sigma_{wn}^2} H (F_R)_{-b} {(F_R)_{-b}}^H H^H \tag{15}$$

In (13), the AP problem of optimization can be decimated in to a chain of sub-problems by selecting the correct initial matrix F_R and assuming that $(F_R)_{-b}$ is fixed. The sub-problem of b-th optimization can be written as in (16)

$$\begin{aligned} &\underset{f_b}{arg\max}\, log_2 \det\left(\mathrm{I} + \frac{\rho\gamma^2}{N_s \sigma_{wn}^2} {f_b}^H H^H {AU_b}^{-1} H f_b\right) \\ &s.t.\quad |f_b| = 1,\ \forall b \end{aligned} \tag{16}$$

Note that maximizing problem (16) over f_b is equivalent to (17)

$$\begin{aligned} &\underset{f_b}{\arg max} \left|{f_b}^H H^H {AU_b}^{-1} H f_b\right| \\ &s.t.\quad |f_b| = 1,\quad \forall b \end{aligned} \tag{17}$$

By defining an intermediate matrix $IM_b = H^H {AU_b}^{-1} H$ helps to solve this problem easily. $f_b(a)$ represent's the a-th element of f_b. Therefore, the following Proposition 1, the proof of it is in Appendix [22], will iteratively obtain every element of f_b.

Proposition 1: Given the elements of AP $\{ f_b(1), f_b(2), \dots, f_b(i), \dots, f_b(N_{T_X})\},\ i \neq a,$
The optimal solution is $f_b(a)$ given in (18)

$$f_b^{optimal}(a) = \varphi\left\{\sum_{\substack{i=1\\i\neq a}}^{N_{T_X}} IM_b{}^H(i,a)f_b(i)\right\} \tag{18}$$

Where the complex parameter is given in (19)

$$\varphi(c) = \begin{cases} 1, & c = 0 \\ \frac{c}{|c|}, & c \neq 0 \end{cases} \tag{19}$$

By Proposition1 one can obtain the optimal solution $f_b^{optimal}(a)$. Computing and calculating AU_b and $IM_b = H^H AU_b{}^{-1}H$ matrices, results in high computational complexity. Specifically, the calculation of IM_b can be simplified by certain standard mathematical operations shown in Proposition 2, given by solution(20), its proof is given in Appendix of [22].

Proposition 2: It is possible to simplify the matrix $IM_b = H^H AU_b{}^{-1}H$, where $AU_b = \mathrm{I} + \frac{\rho\gamma^2}{N_s\sigma_{wn}^2}H(F_R)_{-b}(F_R)_{-b}^H H^H$

$$IM_b = K + \frac{\frac{\rho\gamma^2}{N_s\sigma_{wn}^2}K f_b f_b{}^H K}{1-\frac{\rho\gamma^2}{N_s\sigma_{wn}^2}f_b{}^H K f_b} \tag{20}$$

Where K=$H^H Q^{-1} H$ and Q= $\mathrm{I} + \frac{\rho\gamma^2}{N_s\sigma_{wn}^2} H F_R^H F_R H^H$.

Due to the computation difficulties of conventional approaches in mm-Wave, the research direction has been motivated towards application of intelligence training methods. Many stochastic algorithms are available in literature that can be implemented. PSO is metaheuristic algorithm, robust against local minima's, makes it appealing for real time applications. PSO has been chosen due to ease of implementation and converges in few computations [24]. It has only two parameters i.e velocity and position. To implement HPSO algorithm one need to have proper mapping of precoding parameters to PSO. The HPSO in Algorithm1 performs the search through swarm of particles and updates in each iteration.

Each bird in the swarm is the particle that carries nonzero element of the precoding matrix i.e i[th] particle holds all precoding coefficients $(F_{\boldsymbol{B}}, F_R)$ and portraying these while initialization is only to convey how HP is mapped to particle.

The significant elements of the precoding matrix F_R, which are not zero are mapped to a particle, therefore the particle that has the best value is to be computed for a given objective function. The objective function provides fitness value for every particle. The Particles in the given search space update their velocity and the position using (21), where w_{wei} is inertia weight, K_j is the personal/local best, K_t is the global best search.

$$\begin{aligned} vel_{j,d}\,(t+1) &= w_{wei} vel_{j,d}\,(t) + b_1 n_1\left(K_j - F_{R_{j,d}}(t)\right) + b_2 n_2\left(K_t - F_{R_{j,d}}(t)\right) \\ F_{R_{j,d}}\,(t+1) &= F_{R_{j,d}}(t) + vel_{j,d}\,(t+1) \end{aligned} \tag{21}$$

The inertia weight w_{wei} maintains current direction and controls the impact between the previous and current velocities. The terms b1 and b2 are referred to as the acceleration coefficients (cognitive and social components) which determines the inclination of search. The variables n_1 and n_2 are random numbers which are distributed in the interval [0, 1] uniformly. The b1 component portrays how much a given particle should rely on itself / believe in its earlier memory, whereas the b2 component conveys how much a given particle should rely on its neighbours [24]. When the inertia weight is initially being greater than 1 the particles are biased to explore the search space and if the inertia weight decays to a value less than 1, the acceleration components are given more attention.

The proposed HPSO algorithm in Algorithm 1 presents the strategy in a better manner. Initially the analog precoder/combiner matrices are computed using array response vectors (7). HPSO will iteratively choose the best pair of analog precoding and combining (F_R, W_R), that maximizes achievable rate and in turn maximizes the SE of the system. The components of the AP are modelled until convergence, to achieve the global optimal value. At each iteration, the velocity of agent is adjusted towards the best location and the best agent. In the simulation, each element $f_b(a)$ requires only a few cycles to achieve convergence. Then the DP F_B is computed based on the optimal AP F_R , which improves the system SE. The HPSO implementation is shown in Figure 2.

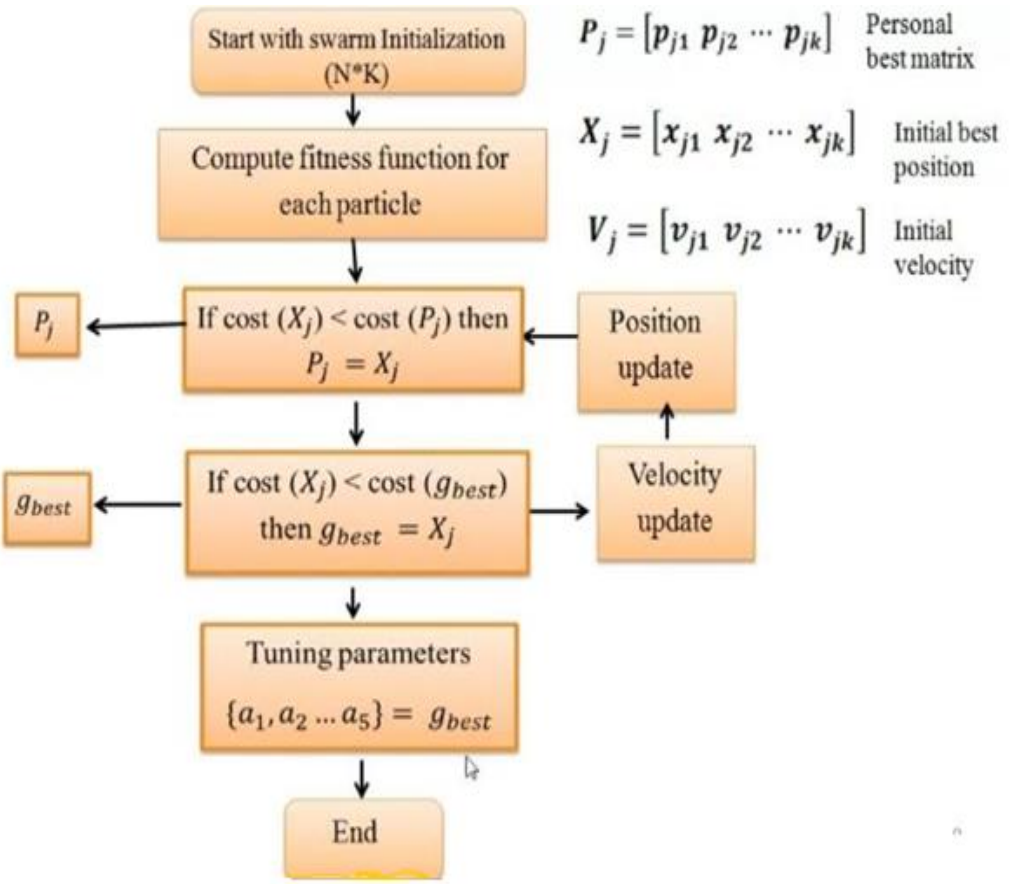

Figure 2: Hierarchical PSO implementation flow chart

1. The individual particle vary their position at each time-step.
2. Algorithm incorporates both local search and global search process for optimization.
3. Each iteration provides a local and a global best position for each particle.
4. As the position of the particle changes, the Velocity of the particle also varies.
5. The particle that has the best solution is tracked and the fitness value is stored in (pbest) best position.
6. The best value tracked by the optimizer by its particle neighbours, is the local best position K_j.
7. The best value when a particle considers all population as neighbours is the gbest, K_t Global best position.

Algorithm1: Hierarchical Particle Swarm Optimization (HPSO) for hybrid precoding

Step1: Initialize the parameters H, K, N_{T_X}, N_s*,i,* ρ
Set F_R *random manner*
For t=1: N_{T_X}
For j=1: size of (K)
If $(F_{R_{j,d}}(t)) < K_j(t)$ *then* $K_j(t) = F_{R_{j,d}}(t)$
$$K_j(t) = \min(K_t(t))$$
End if
For d=1: dimension
$$vel_{j,d}\,(t+1) = w_{wei} vel_{j,d}\,(t) + b_1 n_1 \left(K_j - F_{R_{j,d}}(t)\right) + b_2 n_2 \left(K_t - F_{R_{j,d}}(t)\right)$$
$$F_{R_{j,d}}\,(t+1) = F_{R_{j,d}}(t) + vel_{j,d}\,(t+1)$$

If $vel_{j,d}(t+1) > vel_{max}$ *then* $vel_{j,d}(t+1) = vel_{max}$
Else if $vel_{j,d}(t+1) < vel_{min}$ *then* $vel_{j,d}(t+1) = vel_{min}$
End if
If $F_{R_{j,d}}(t+1) > F_{R_{max}}$ *then* $F_{R_{j,d}}(t+1) = F_{R_{max}}$
Else if $F_{R_{j,d}}(t+1) < F_{R_{min}}$ *then* $F_{R_{j,d}}(t+1) = F_{R_{min}}$
End if
End for
End for
End for
Step2: l=0;
Step3: repeat
Step4: for b=1 to N_s
Calculate fitness function f_b *from* ${F_R}^l$
Update $IM_b = K + \frac{\frac{\rho\gamma^2}{N_s\sigma_{wn}^2} K f_b {f_b}^H K}{1 - \frac{\rho\gamma^2}{N_s\sigma_{wn}^2} {f_b}^H K f_b}$

While no convergence of $f_b(a)$ *do*
For a=1 to N_{T_X}
$$f_b(a) = \varphi \left\{ \sum_{\substack{i=1 \\ i\neq a}}^{N_{T_X}} {IM_b}^H(i,a) f_b(i) \right\}$$
End for
End while
Compute ${f_b}^{l+1}$ *by using* $\{f_b(a)\}_{a=1}^{N_{T_X}}$
End for
Compute ${F_R}^{l+1}$ *by using* $\{F_R(a)\}_{a=1}^{N_s}$
l=l+1;
Until a stop criterion is activated
Step 5: compute F_B

Where $w_{wei} = 0.5 + \frac{[0 \; or \; 1]}{2}$ is the inertia factor, b_1 & b_2 are constant values and n_1, n_2 unifor mly distributed random value.

Even though PSO is simple to implement, it is not that easy to obtain optimality conditions for very large datasets. Hence, the variations of the PSO algorithm or incorporation of deep learning is needed in future to work with the real time datasets.

3.4. Hybrid Combiner Design

The design of hybrid combiner follows same as HP to optimize the overall SE in (5). The appropriate formulation of the problem is given in (22)

$$\underset{W_B, W_R}{arg\,max}\ \log_2 \det\left(\mathrm{I} + \frac{\rho}{N_s} R_n^{-1} W_B^H W_R^H H_1 H_1^H\ X\ W_R W_B\right) \tag{22}$$
$$\text{s.t } |W_R(a,b)| = 1 \quad \forall a, b$$

Where $H_1 = H\ F_R\ F_B$. The analog combiner also satisfies $W_R^H W_R \propto \mathrm{I}$ for the antenna-arrays in large-scale [22], close to the AP. Therefore, assuming $W_B W_B^H \approx \delta^2 \mathrm{I}$, where δ^2 factor of normalization, obtains the value $W_B^H W_R^H W_R W_B \approx \mathrm{I}$. The objective function in (22) can be approximated as given in equation (23)

$$= \log_2 \det(\mathrm{I} + \frac{\rho}{N_s} R_n^{-1} W_B^H W_R^H H_1 H_1^H W_R W_B) \approx \log_2 \det\left(\mathrm{I} + \frac{\rho}{N_s \sigma_{wn}^2} W_B^H W_R^H H_1 H_1^H W_R W_B\right) \tag{23}$$

The digital combiner is modelled for a fixed analog combiner according to the proposed hierarchical strategy. It is possible to write the virtual combiner design problem given in (24) as

$$\underset{W_B}{arg\,max}\ \log_2 \det\left(\mathrm{I} + \frac{\rho}{N_s \sigma_{wn}^2} W_B^H W_R^H H_1 H_1^H\ X\ W_R W_B\right) \tag{24}$$

By applying the singular value decomposition (SVD) of $H_1^H W_R$ i.e $H_1^H W_R = U_1 \Lambda_1 V_1^H$, the solution of W_B design is given in (25)

$$W_B = V_1 \tag{25}$$

Since W_B is an unitary matrix, the previous assumption of W_B^H is valid. Appropriately the analog combiner W_R design problem in (23) can further given as (26)

$$\underset{W_B}{arg\,max}\ \log_2 \det\left(\mathrm{I} + \frac{\rho\delta^2}{N_s \sigma_{wn}^2} H_1^H\ W_R W_R^H H_1\right) \tag{26}$$
$$s.t\ |W_R(a,b)| = 1 \qquad \forall a, b$$

This analog combiner W_R is similar to AP problem in (12). To achieve the ideal W_R , the symbols F_R and H are replaced by W_R and H_1 in Algorithm1.

4. Simulation Outcomes

The HPSO performance with the existing algorithms are illustrated for $N_{T_X} = 144,\ N_{R_X} = 36$ in mm-WmM. The UPA is particularly suitable for mm-Wave MIMO systems due to its favourable propagation performance and compact physical size. The propagation channel environment is modelled with $S_{clu} =$ 5 clusters with $P_{path} = 10$ rays per cluster, according to [19]. AODs and AOAs observe the Laplacian distribution of azimuth and elevation angles over $[0, 2\pi)$ with uniformly distributed mean angle and a spread of 10 degrees. The SNR = $\frac{\rho}{\sigma_{wn}^2}$, enforcing identical total power constraint for uniformity on all precoding algorithms. The results are illustrated for 1000 random channel realizations on an average. The parameters for HPSO Algorithm are in Table 1.

Table 1. HPSO Algorithm parameters

PSO Parameters	Values
Swarm Size (Population size)	50
Inertia Weight w	1
Wdamp	0.99
Acceleration coefficient-Personal b1	1.5
Acceleration coefficient-Global b2	1.5
Maximum number of Iterations	1000

A. Evaluation of Spectral efficiency(SE)

Consider the perfect CSI, the SE with different algorithms is investigated. To reduce the energy cost of the mm-WmM , assume NRF is equal to the Ns. As illustrated in Figure.3, the SE of the Optimal, Proposed, RF-Iterative algorithm [13], PE-AltMin algorithm [19], OMP [14], Analog beamforming [10] are plotted and compared. With regard to SE, in the case of fully connected HPC structure shown in Figure.1, provides more freedom in the RF domain and the proposed HPSO algorithm is capable of achieving near-optimal digital precoding/combining performance. The SE increases as SNR varies from -30dB to 5dB, indicates that mm-WmM can overcome channel impairments and noise.

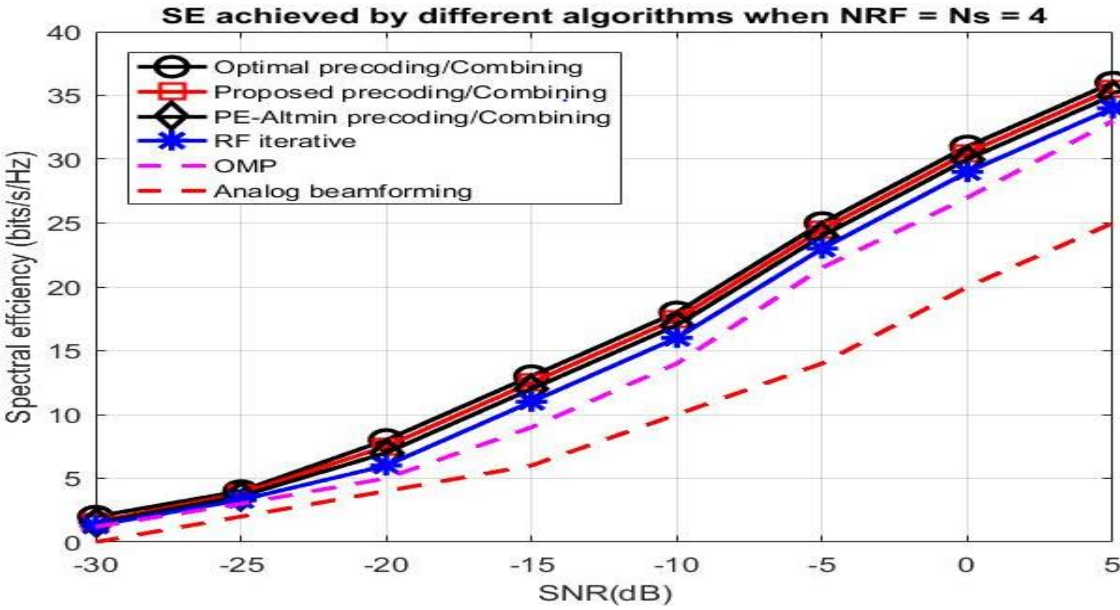

Figure 3: SE vs SNR for different algorithms for $N_{T_X} = 144,\ N_{R_X} = 36$

This means that the proposed algorithm is preferable compared to other algorithms, even though the N_{RF} are limited. The HPSO algorithm outperforms the existing ones which makes it suitable for implementation in a practical mm-Wave MIMO system. The OMP algorithm is sensitive to the choice of dictionary matrix and its dependence on sparsity knowledge leads to its poor performance.

For investigating the convergence of the HPSO, the SE versus no. of iterations is plotted in Figure.4. The main short coming of the OMP is that small modification of stopping criterion or any violation in constraints of dictionary matrix leads to its convergence errors i.e it's performance is not robust. It is observed that the convergence of the HPSO algorithm is faster than the existing algorithms and has a major implementation benefit for the realistic scenarios.

In the practical mm-WmM, it is very tough to obtain perfect CSI due to the high dimension of the channel matrix. Hence, it is important to evaluate the performance of the proposed HPSO algorithm under the imperfect CSI as shown in Figure.5.

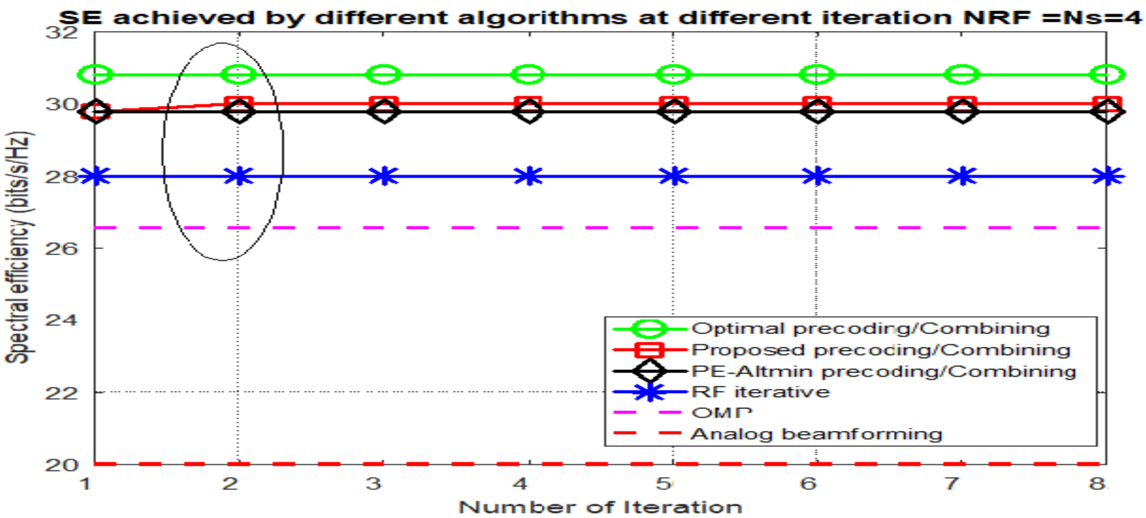

Figure 4: SE vs no. of iteration by different algorithms (Lt=Lr=NRF=Ns=4) and SNR=0dB

The estimated approximate channel matrix for imperfect CSI is then referred to as $\hat{H}$, which can be expressed as (27)

$$\hat{H} = H\tau + \sqrt{1-\tau^2}\text{EM} \tag{27}$$

Where EM is the error matrix which is i.i.d with (0,1) mean=0, variance=1 , $\tau \epsilon$ [0,1] represent the channel estimation accuracy. In Figure.5, consider the imperfect CSI scenario with various τ values, evidently the HPSO algorithm performance increases when τ grows larger. It is observed that the proposed HPSO algorithm is robust i.e it is insensitive to the varying accuracy of CSI, which is an added advantage. It is also observed that when $\tau = 0.9$ the HPSO instantly gets closer to the perfect CSI case. For $\tau = 0.5$ also it achieves an acceptable performance.

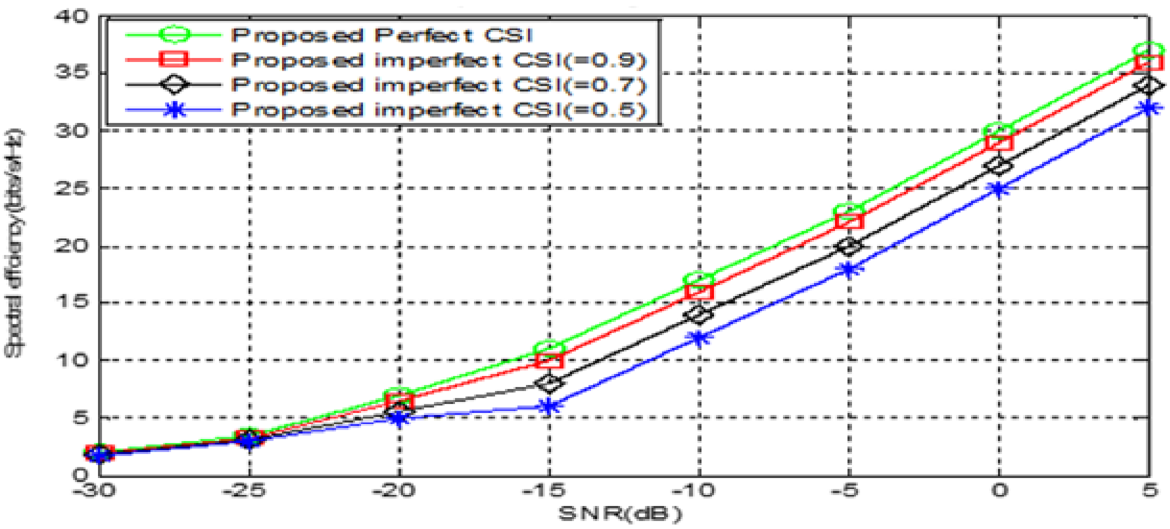

Figure 5: Impact of imperfect CSI on HPSO algorithm (NRF=Ns=4)

In Figure.6 and Figure.7, the N_{T_X} and N_{R_X} are varied and the SE is plotted at SNR = -20dB. It shows the performance enhancement by the HPSO algorithm over the existent ones and approaches the optimal performance. HPSO has a SE almost 40 bps/Hz more than the Analog beamforming with $N_{T_X} = 144$, $N_{R_X} = 36$. One of the reasons for the improved performance is that it is possible to form narrower beams by RF antenna arrays with larger number of antennas at the Tx and Rx. It significantly contribute towards improving the total achievable SE, which is especially appealing for mm-Wave massive MIMO systems.

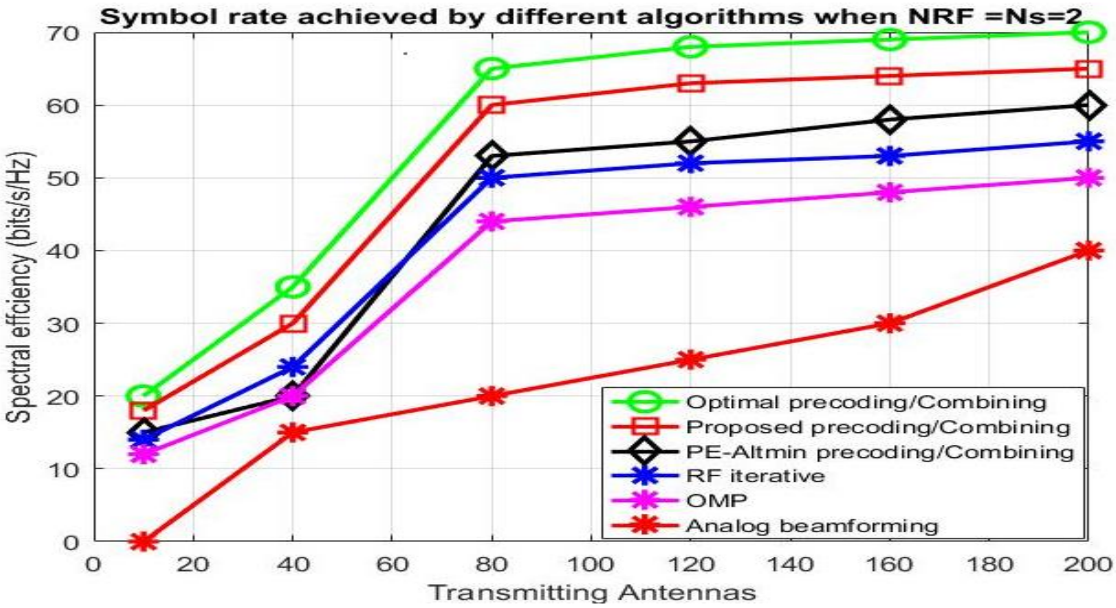

Figure 6: SE vs Transmitting antennas

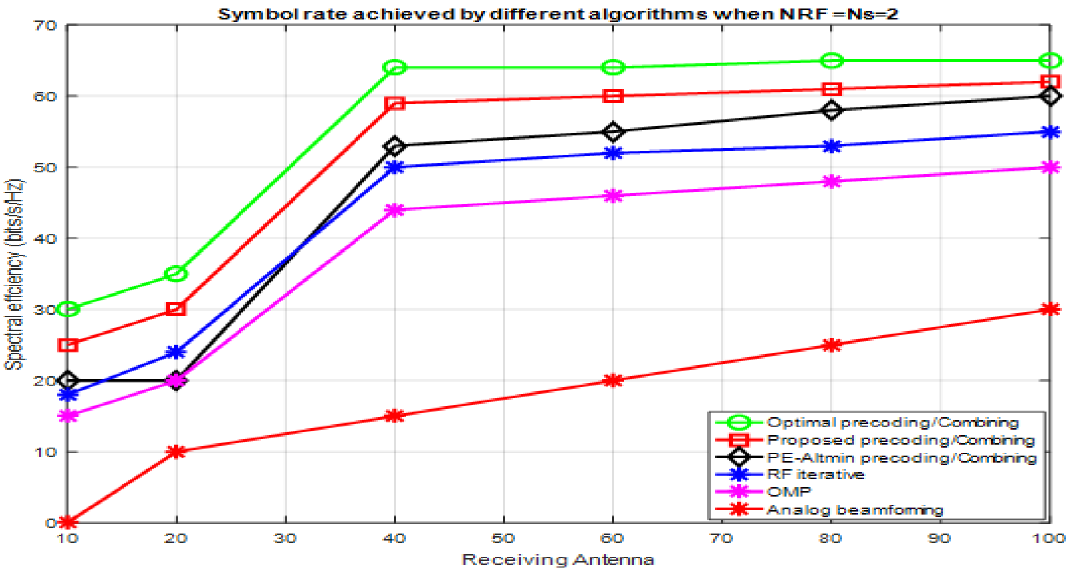

Figure 7: SE vs Receiving antennas

5. Conclusion

The HPC in mm-Wave MIMO systems are examined in this paper by incorporating AI based algorithm. To optimize the AP, the HPSO algorithm is proposed and based on optimized AP the optimal DP is calculated. The hybrid combiner is designed using similar hierarchical strategy as hybrid precoder. The simulation and the low computation analysis shows that the algorithm proposed could achieve almost optimal performance. The design of hybrid precoder along with sparse channel estimation in mm-WmM can be improved by incorporating Deep learning intelligence algorithms for real time datasets in future.

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