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Beam Squint and Channel Estimation in MM Wave Massive MIMO-OFDM Systems based on Multi Layer Perceptrone

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ABSTRACT. The usage of cellular data has been growing at a staggering pace today, by analysing this incredible growth implies that within the next decades, cellular networks need to deliver as much as thousand times the capacity relative to current levels. For the fifth generation (5G) cellular networks Millimeter - wave (mmWave) communications have been widely recognized as a promising technology, compensate severe path loss in mmWave transmission. Sufficient array gain is employed by the massive multiple-input multiple-output (MIMO) technology. Where in massive MIMO there are more number of input and output antenna array for the transmission of data. However, the mmWave massive MIMO communications encounter a problem in which different antennas receive differently-delayed versions of the same signal which is due to the large array aperture. And the phenomenon is been termed as the spatial wideband effect. For an orthogonal frequency division multiplexing (OFDM) system, for different subcarriers to "see" different angles of arrival (AoAs) for the same physical path due to the spatial-wideband effect. Hence, here the existing wideband mmWave massive MIMO working by the identical beamforming vector deploying over all of the subcarriers actually formulate these beams towards different physical directions, such an effect is named as beam squint. OFDM is used in the wireless communication for high quality data transmission. Channel estimation done by Multilayer Perceptrone (MLP), artificial neural network, with more than one perceptron in structure. Among the three layers, input layer to receive the signal, output layer makes a decision about the input, and arbitrary number of hidden layers, for the true computations of the MLP. It trains on a set of input-output pairs and then learns to model the dependencies in between those inputs and outputs. Training includes adjusting the weights and biases. Backpropagation algorithm is used to make those weight and bias adjustments. The superiority of proposed over the conventional scheme is demonstrated by graphical and numerical results under different general system configurations in the massive mmwave communications.

KEYWORDS *:* Beam Squint Effect, Spatial Wideband Effect, Multilayer Perceptrone, Back Propagation.

I. INTRODUCTION

Wireless communication technology is generally utilized in the current decade, with wide frequency band mmWave communication is more dependable. Wireless networks empowers remarkable gigabits-per-second data transmission and quickly developing demand of wireless traffic can be fulfilled. In mmWave [1] bands radio signals experience path loss effect and powerless diffractive capacity.. Among them Massive multiple-input multiple-output (MIMO) technology is applied where spectral and energy efficiencies can be improved. MIMO methods can significantly wireless system capacity without requiring any additional transfer speed. MIMO can offer, a precise channel state information , which is needed at the transmitter and reciever. A major part in MIMO is played by an exact channel estimation, is generally done by employing traning sequence (pilot signals) [2] , and channel

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estimation by the data and trained sequences.. For high data rate and quality in communication system, here uses orthogonal frequency division multiplexing (OFDM), where the total signal bandwidth is divided into the number of sub carriers. Various antennas may receive different time-domain symbols from a similar physical path, these symbols undergo large propagation delay known as spatial wideband effect which only considersphase difference and ignores delay difference.

Here , distinct angles of arrival (AoAs) [3], for a similar path will be seen for various subcarriers in an OFDM system. This outcomes from spatial-wideband effect , which is known as beam squint. In consideration between beam squint and the spatial wide band effect, proposes a channel estimation method, for massive MIMO-OFDM systems dependent on hybrid precoding. The level of beam squint and spatial wide band effect are always proportional. Channel estimation dependents on pilot information signals with Least square (LS) and minimum mean square error (MMSE) estimations. This paper, has a neural netwok class, multi layered perceptrons (MLP) [4] with backpropagation (BP) algorithm for estimating channel in OFDM systems. Artificial neural networks are data handling patterns which are motivated by human nervous system.. It utilizes Adaptive Learning where, customization of resources are done for unique needs. Among the three layers, input, hidden and output, hidden layer adjusts the synaptic weights. MLP has two phases as training stage and testing stage, for collection of data and accessing network performances respectively.

The incredible growth in wireless communication system[5] implies that the in the upcoming decades, cellular networks will be forced to deliver need to deliver more than 1000 times the capacity to present levels. mmW signals with wavelengths from 1 to 10 mm, frequency in the range of 30–300 GHz will provide a great support for fastest communication. This follows a standard methodology for placing the BSs and UEs are randomly according to particular statistical model, for network realizations. In massive MIMO systems optimal pilot design is based on channel estimation [6] where, the number of antennas are increased to a value, till the pilot contamination is been nil, hence the signal to noise and noise ratio will not increase. Numerous techniques were introduced for eliminating pilot contamination, aimed to high the signal-to-noise ratio (SNR). In massive MIMO systems optimal pilot sequences design is done in order to eliminate the pilot contamination, and a channel estimation scheme based on pilot design is done. Wideband channel estimation for frequency division duplex system in mmwave massive MIMO [7]is done by analyzing the channel model with frequency dependent steering vector considering beam squint. In a FDD system small amount of training and user feedback is required for channel parameters using super resolution sensing algorithm.LS and MMSE estimation techniques are performed for depicting channel properties by considering the error rate. As a modulation scheme orthogonal frequency division multiplexing is used for high data rate communication systems [8] where for coherent demodulation channel impulse responses to be estimated at receiver side. Where estimation is done with back propagation algorithm by multilayered perceptrons (MLP) neural network. MLP has better performance than LS algorithm and the better channel impulse responses. By using this method it is not necessary to get the channel statistics, noise information and matrix computation for channel estimation.

The rest of this paper is as follows: Section II proposes the wideband massive MIMO-OFDM systems with beam squint and its characteristics. Section III introduces the system model considering beam squint. Section IV with uplink channel parameters. Section V with downlink channel parameters , section VI gives the simulation results and Section VII concludes this paper.

II. MASSIVE MIMO SYSTEM WITH BEAM SQUINT EFFECT

Consider F number of single-antenna, and a base station (BS) where antennas are users distributed throughout the cell randomly in a mmWave [9] massive MIMO-OFDM system. Here U is the antenna uniform linear array (ULA) and the antenna spacing is s in BS. In orthogonal frequency-division multiplexing (OFDM) [10] , multipath delay spread is with B_c subcarrier with D as the transmission bandwidth. Subcarrier spacing over here is as $\eta = D/B_c$. The multipath delay and t propagation delay of electromagnetic waves is combated by the long enough cyclic prefix (CP). travelling across the whole antenna array. The fth user has u_f incident paths from to the BS. Time delay can be denoted as $\tau_{f,k,u}$ as the kth path from the fth user to the uth antenna of the BS and denote $T_{f,k} \triangleq T_{f,k,u}$ for the simplicity ,where the value $u \in \{1, \ldots ,U\}$ and $f \in \{1, \ldots , F\}$, $u \in \{1, \ldots , u_f\}$. AoA of the kth path from the fth user is $\vartheta_{f,k}$ and define normalized AoA as $\psi_{f,k} \triangleq \frac{s \sin \vartheta_{F,k}}{\square_c}$, where carrier wavelength is λ_c.

The antenna array sizes are much smaller than the distance between the transmitter and the receiver according to the far- field assumption.

$$T_{f,,k,u} = T_{f,u} + (u\text{-}1)\frac{s \sin \vartheta_{F,k}}{g} = T_{f,i} + (u\text{-}1)\frac{\vartheta_{F,k}}{f_c} \tag{1}$$

Where $f_c = \frac{h}{\square_c}$ is the carrier frequency and c is the speed of light. The complex channel gain , $\alpha_{f,k}$ of the kth path from the f th user. Then, the expression for impulse response of the uplink channel between the fth user and the uth antenna at the BS can be as :

$$h^{T}_{f,l} = \sum_{i=1}^{Ik} \alpha_{f,k}\, e^{-j2\pi(u-1)\psi_{F,k}} \delta(t - T_{f,k,u}) \tag{2}$$

Consider the Fourier transform of (2), the frequency response at the BS between the kth antenna and the fth user can be as:

$$h^{F}_{f,m}(f) = \sum_{u=1}^{ik} \alpha_{f,m}\, e^{-j2\pi(M-1)\psi_{F,k}\left(1+\frac{F}{F_c}\right)} e^{-j2\pi f T_{F,k}} \tag{3}$$

mmWave massive MIMO-OFDM [10] systems shows Discrete Fourier transform (DFT) transforms to virtual angle domain for

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obtaining the following theorem, considering the beam squint effect. Stacking all $h^F(f)$'s into a vector yields from different antennas:

$$h_k^F(f) \triangleq \sum_{u=1}^{U_k} \alpha_{k,u}\, f(\Xi_{k,u}(f)) e^{-j2\pi f T_{k,u}} \tag{4}$$

It gives the spatial-domain steering vector with wideband by proposed model depicted in massive MIMO-OFDM channel. Different from the widely-used mmWave models, by considering the frequency dependent steering vectors, which is referred to as the beam squint effect. By a matrix by mathematical manipulations the channel of the fth user can be arranged as:

$$H_f^F(f) = \sum_{l=1}^{I_k} \alpha_{f,i}\, f(\Xi_{f,i}(f)) f_U^H(\Xi_{U,f,i}(f)) e^{-j2\pi f T_{f,i}} \tag{5}$$

By taking beam squint over OFDM subcarriers, the channel between the ath user at the yth subcarrier and BS can be:

$$h_{f,y} \triangleq \sum_{i=1}^{I_k} \alpha_{f,k}\, f(\Xi_{f,k}((y-1)\square))\, e^{-j2\pi(y-1)\square T_{Fk}} \tag{6}$$

The squint over all subcarriers for ith path can be expressed as:

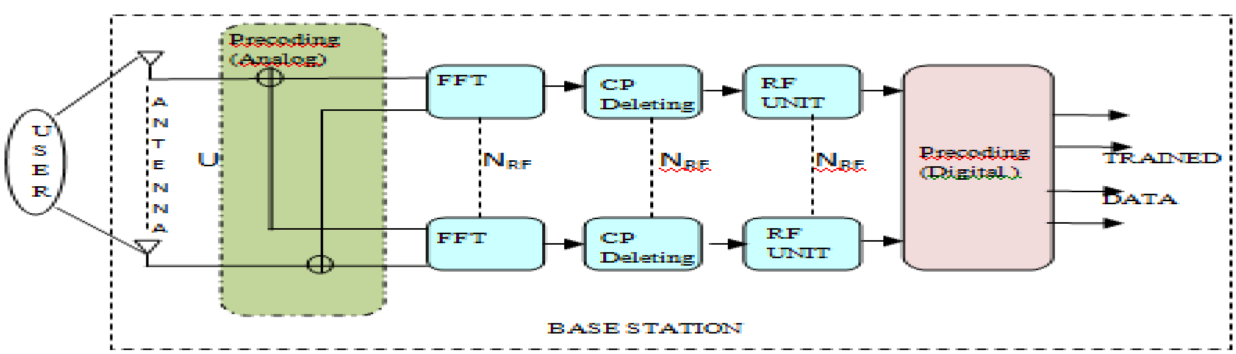
$$|v_{1,S_c} - v_{k,1}| = L\psi_{f,k} \frac{(S_c-1)\square}{f_c} = \left(L\frac{s \sin v_{f,k}}{\square c f_c}\right)B \cong \frac{T^{prop}_{f,k}}{T_s} \tag{7}$$

The relationship between the beam squint effect and the spatial-wideband effect indicates that can use the propagationdelay in samples, $T^{prop}_{m,u}$, where the beam squint level is determined.

III.SPATIAL WIDEBAND EFFECT BASED SYSTEM MODEL WITH METHODOLOGY

Considers the spatial wide band effect derives the wideband mmWave massive MIMO channel model. The hybrid analog/digital precoding and the full-digital systems share the same channel model. Consider the mmWave systems under the phase shifter-based hybrid architecture. Let the BS have N_{RF} radio frequency (RF) chains. Employ successive OFDM blocks for uplink channel estimation as T_{up} . For the zth subcarrier and the dth block the hybrid precoder at the BS can then be denoted as $\mathbf{W}_{z,d} = \mathbf{W}_{RF,d}\,\mathbf{W}_{BB,z,d} \in \mathbb{C}^{L\times N_{RF}}$, where $\mathbf{W}_{RF,d} \in \mathbb{C}^{L\times N_{RF}}$ is the phase shifters implemented analog combiner by at the d th block and $\mathbf{W}_{BB,z,d}$ is the digital baseband combiner at the z th subcarrier and the b th block. Here each user assigned with P of S_c subcarriers as pilots and the pilot subcarrier indices [11] set for the f th user, the received signal vector at the BS in the z th subcarrier at U antennas can be expressed as:

$$Z_{f,z,d} = B^H_{f,d}\, x_{f,z,d} + W^H_{f,d}\, n_{f,z,d} \tag{8}$$



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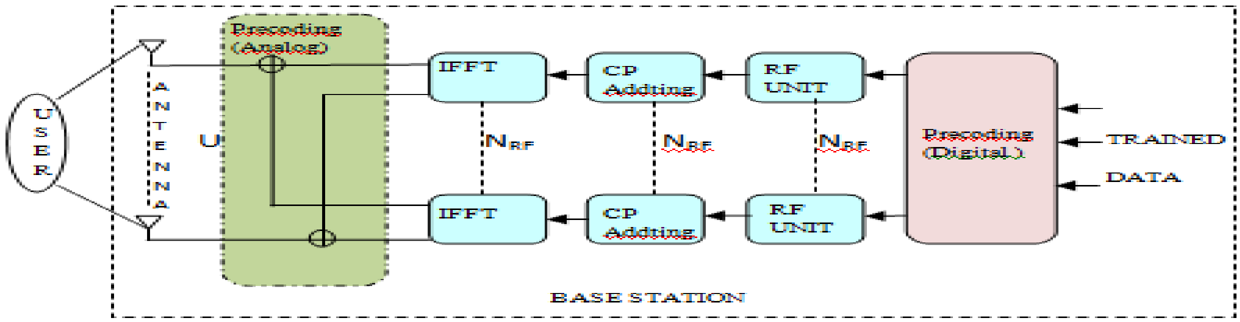

FIGURE 1. Uplink And Downlink Block Diagram

Here, $x_{f,z,d}$ implies the pilot symbol from fth user at zth subcarrier in the dth block with a Gaussian noise where each element is independently distributed. The pilot symbols are known for both users [12], [13] and base station:

$$y_{m,q} \triangleq \left[\frac{1}{x_{m,q,u}} y^T_{m,q,1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \frac{1}{x_{m,q,u,T_{up}}}\right] = W^H h_{m,q} + W^H \square \tag{9}$$

q

q

m

,

q

$$W_q \triangleq [W_{q,1}, \ldots\ldots\ldots W_{q,T_{up}}] \epsilon\, \mathbb{C}^{I x\, N_{RF}\, T_{up}}$$

Then

$$y_m \triangleq [y^T_{m,p_m,1}, \ldots\ldots\ldots\ldots\ldots, y^T_{m,p_m,m}]^T = W^H h_k + n_k$$

$$W \triangleq \begin{bmatrix} W_{p_m,1} & 0 & \cdots & 0 \\ 0^n & W_{p_m,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W_{p_m,T_{up}} \end{bmatrix} \epsilon\, \mathbb{C}^{MP\, X\, NRF\, PTup} \tag{10}$$

$$h_m = P_m(\psi_m, m)\, \alpha_m \tag{11}$$

A sparse representation is given by h_m which is of the basis above that considers the beam squint effect. By using AoA-delay reciprocity covariance matrix of downlink channel can be reconstructed with the parameters (physical) of the uplink channel.

III. CHANNEL ESTIMATION UPLINK

At initial uplink channel parameter extraction, at the beginning the BS does not know about the channel state information and the user locations, hence apply orthogonal trainings to minimize inter-user interference and pilot degrading at the BS. Estimation of each path's initial AoA, time delay, and complex gain for all users is at the initial parameter extraction phase. For this stage, where for the subsequent multi-user uplink and downlink channel estimations [14] is sufficed a parameter extraction algorithm is introduced, with a data signal obtained from the OFDM receiver with a data set dimension size of 128 x 7680. The uplink pilots transmission process for the f th user is:

$$yf = B^H P_f(\psi_f.\tau_f)\alpha_f + n_f. \tag{12}$$

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Here extracts these physical parameters, $\{\psi_f, \tau_f, \alpha^a\}$, from yf. The powerful tool where the number of the parameters is fewer than the dimension of yf, i.e., 3uf□□□ N_{RF}PTup, is compressive sensing algorithm, thus parameter extraction problem can be reduced. Proposes a compressive sensing-based off-grid approach [15] for obtaining the physical parameters. Here the problem formulation can be as:

$$\min_{\psi,c,\beta} \|\beta\|_0 \quad \|z_f - B^H P_f(\psi,\tau)\beta\|_2 \leq \xi \tag{13}$$

Here the error tolerance is controlled by ξ, related to the noise statistics the number of nonzero entries of vector β, □□β□□$_0$ and its a small positive number. Initial physical parameters are obtained , then with a small amount of training uplink and downlink channels can be estimated. During initial parameter extraction phase AoAs and path delays of a user obtained depending on its moving speed. Hence need update only the channel gains. Finally, AoAs and path delays can be directly applied in downlink channel estimation. Only the channel gains need to be fed back to the BS for reconstructing the downlink channel:

$$D_u(h_{f_1}, h_{f_{21}}) \triangleq \min_{k_1,k_2} [\, \|[\, L(\psi_{1,k1,})P□r_{f_1 k_1}]^T [\, l(\psi_{f2,k2,})P□r_{f_2 k_2}]^T \|_2 \,] \tag{14}$$

LS estimate can be as:

$$\hat{\alpha}_{u,S} = (B^H_y P_f)^{\dagger} z_y = (P^H_f B_y B^H_y P_f)^{-1} P^H_f B_y v_y \tag{15}$$

As for all N_c subcarriers channel basis, define $\tilde{P}_f = [\tilde{P}(\psi_{f,k} r_{f,k}), \ldots\ldots\ldots\ldots \tilde{P}(\psi_f\, r_{f,} K_{f,})]$ a users uplink channel on all subcarriers can be reconstructed as:

$$h_{f,LS} = \tilde{P}_f \tilde{\alpha}_{f,LS} \approx \tilde{P}_f \alpha_{f,LS} \tag{16}$$

After considering different same group users, the MSE values can be estimated as:

$$\tilde{h}_{f,MMSE} = \tilde{P}_f \Lambda_f P^H_f B_y (B^H_y \sum_{r \in G_y} R_r B_y + \sigma^2_n C_{n_y})^{-1} z y \tag{17}$$

V. DOWNLINK CHANNEL ESTIMATION

Downlink channel can be obtained by reciprocity between uplink and downlink, not for FDD systems. With less user feedback and low training overhead a downlink channel estimation strategy is designed. In conventional cases each multipath delay can simply use a single RF chain to generate a beam towards the specified direction. A beam is generated over different subcarriers should generate a beam after considering the beam squint effect, frequency-dependent beam-

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steering vectors [16]. The signals will not reach the specified users if ignoring beam squint will in certain frequencies is done.

A. Downlink Channel Model and User Grouping

Here the downlink carrier frequency is f_c^O and wavelength is $\lambda_c^O = 1/ f_c^O$. Then downlink channel as:

$$h_f^O = BP_f(\psi_f^O, \tau_f)\alpha_f^O \tag{18}$$

From the uplink version extracted in initial parameter extraction phase ψ_m^D can directly computed as:

$$\psi_{m,u}^D = \frac{d\sin\vartheta_{m,u}}{\lambda_c^D} = \frac{f_c^D}{f_c} = \frac{d\sin\vartheta_{m,u}}{\lambda_c}\frac{f^D}{f_c} \text{ mul} \tag{19}$$

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The user does not know the path delays and does not synchronize with each other, terms ofAoAs. Here by stacking all steering vectors in Aorth into a matrix designing of the analog precoder, [17] **F**RF ∈ C $^{L\times|Aorth|}$ is done, matrix with each column being one steering vector in Aorth. The **F**BB,y which is the digital precoder at the yth subcarrier, is a diagonal matrix as:

$$\mathrm{Diag}(F_{BB,q}) = F^{\dagger}_{RF}(\sum_{k\epsilon \mathcal{G}_y^D} B_{m,q})c_q \tag{20}$$

B. Downlink Channel Estimation with LS or MMSE estimator

Let $\mathbf{z}_f \triangleq [z_{f,1}, \ldots, z_{p,P}]^H \in C^{P\times 1}$ and pilot subcarriers are all 1's as assumed for simplicity. In the same group by using the asymptotical orthogonality between different user channels, the of downlink complex gains of LS estimate can be obtained as:

$$\tilde{\alpha}_{f,LS} = (C^H)^{\dagger} g_f \tag{21}$$

The downlink channel covariance matrix can be constructed by considering **P**f (ψf,**τ**f) replaced by **P**f(ψ^D_f **τ** f) and from the average of previous estimated gains **Λ**f can be calculated . The downlink complex gains MMSE estimate can be determined as:

$$\tilde{\alpha}_{f,MMSE} = \Lambda_f (P^O_f)^H i \textstyle\sum_i + \sigma^2 T_n \, k_{ok} \,)^{-1}_P z_f \tag{22}$$

C. Mlp Neural Network With Back Propagation For Channel Estimation

The backpropagation (BP) algorithm is based on nonlinear LS optimization method[18]. Here O(t) is the objective function , the aim is to minimize O(t):

$$O(t) = ½ \sum_{l=1}^{u}(Li - Bi)^2 \tag{23}$$

Where pth expected output as Li , pth obtained output as Bi and number of output points as u. Updates the weight of network as:

$$\Delta w = \text{input} * \eta * O(t) \tag{24}$$

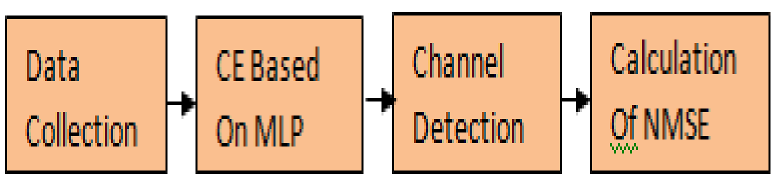

FIGURE 2. MLP Block Diagram

Here to obtain the correct output represented as η ,the learning rate which changes the weight. Determining the efficiency of the network is by learning rate. The objective function changes the learning rate parameter accordingly . with high learning rate higher is the network training. A NN channel estimator consists of three layers . these layers are namely the input layer, hidden layer and output layer where hidden layer consisting of P2 neurons and input and output with P1 neurons. Backpropogation [19], [20] is done through these hidden layers where the weight is been adjusted to get the desired result.The complex OFDM signals are splitted into real and imaginary parts as NN requires only real signals. Working process includes the followings: tangent sigmoid activation function is applied after the input signal and weights are multiplied. The activation function is:

$$net_j = \sum_{i=0}^{P1} Si\ Tij$$

Where the weight between input, T_{ij} and hidden layer at jth node together with P1 denotes number of input neurons :

$$N_j = f(netj) = (e^{netj}-1)\ (e^{netj}+1) \tag{26}$$

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The output layer's activation function is given by:

$$\mathrm{Net}_k=\sum_{j=1}^{P2} Nj\ Tjw \tag{27}$$

$$N_w = f\ (\mathrm{net}_w)$$

Where Tjw is weight between hidden layer and output layer at wth node and P2 denotes number of hidden layer nodes. The output of the neural network estimator is given by:

$$N_w=f(\mathrm{net}_w)f(\sum_{j=0}^{P2} Tjw\ \ f\ (\sum_{i=0}^{P1} Tij\ \ f(\mathrm{Si\ tij}))) \tag{28}$$

VI. STIMULATION RESULTS

This section provides the performance evaluation of the system by analyzing numerical results where the necessity of carefully treating the beam squint effect is considered. Proposed approaches under practical mmWave massive MIMO system configurations are validated. In Fig. 3, The conventional method fails in extracting path AoAs and delays with the increase in squint level, conventional method assumes that at different subcarriers are the same when the observed AoAs is considered . Here effect, where the performance gets worse with increase in number of antennas and/or higher bandwidths, which will be shown in the subsequent numerical results. NMSE of MLP estimation versus the received signal-to-noise ratio (SNR). Here , we consider the single-user scenario to exclusively depict the effect of beam squint.As the more BS antennas, the proposed approach has the exceptional estimation performance. However, the approach ignoring the beam squint effect has to suffer from severe performance degradation as increasing with the number of the BS antennas.

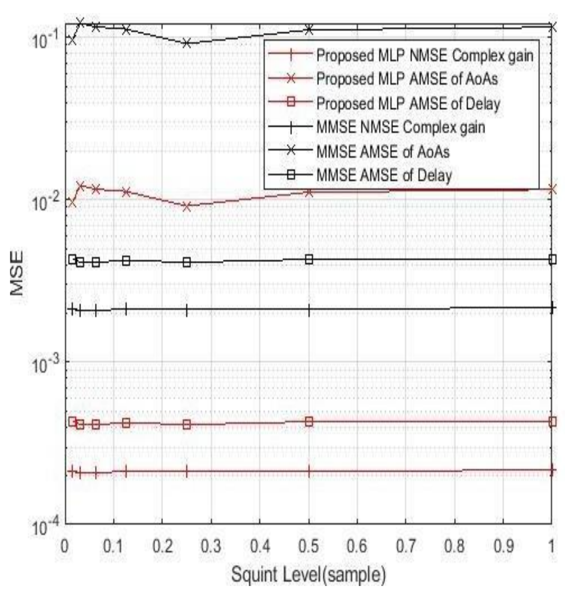

FIGURE 3. MSE of Beam Squint Level Versus Initial Parameter Extraction

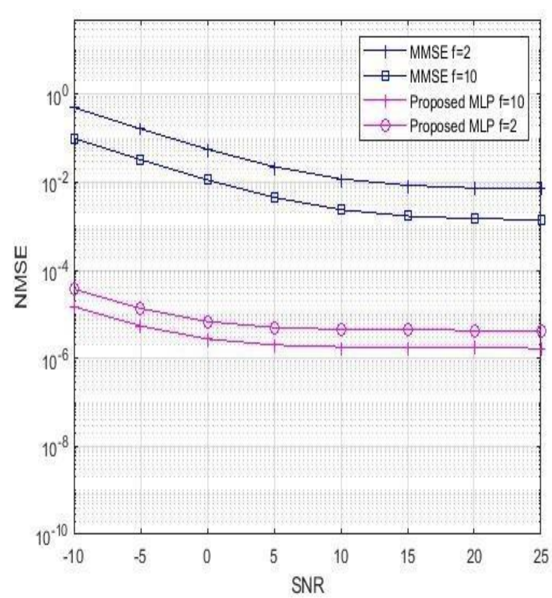

FIGURE.4 . NMSE of MMSE Estimation For SNR Under Different Number Of antennas

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Fig. 4 compares the MMSE estimator and MLP in uplink channel estimation. Here the number of the shared pilot subcarriers and the BS antennas and are set and P = 12 and U = 32, respectively. The uplink guard interval is ΩU = 5. Since the number of users that share the same pilot subcarriers evaluates the performance instead of the total number of users, for of frequency reuse or sharing investigation. Here number of antenna is as 2 and 10 respectively, and provide the corresponding results with considering beam squint to error rate and signal to noise ratio.

VII.CONCLUSION

This paper discusses the beam squint effect and propose a FDD mmWave massive MIMO systems wideband channel estimation strategy with multi layer perceptrone. An assistance of pilot symbols gives channel impulse responses. The frequency sensitive and frequency insensitive parameter extraction is done for uplink and downlink channel estimations. The networks are trained using channels impulse responses. The trained networks in MLP is utilized as a channel estimator here together with MMSE estimator. Performance of MMSE and NN using back propagation algorithm estimation technique is compared. MLP, a class of neural network estimator shows performance as good as the transmission case also with perfect channel impulse responses compare to MMSE estimator. Comparison over these techniques done by giving different parameters different values. Finally, the superiority of the proposed channel model and channel estimation strategies over algorithms based on the conventional MIMO models under general mmWave system configurations are demonstrated by numerical results.

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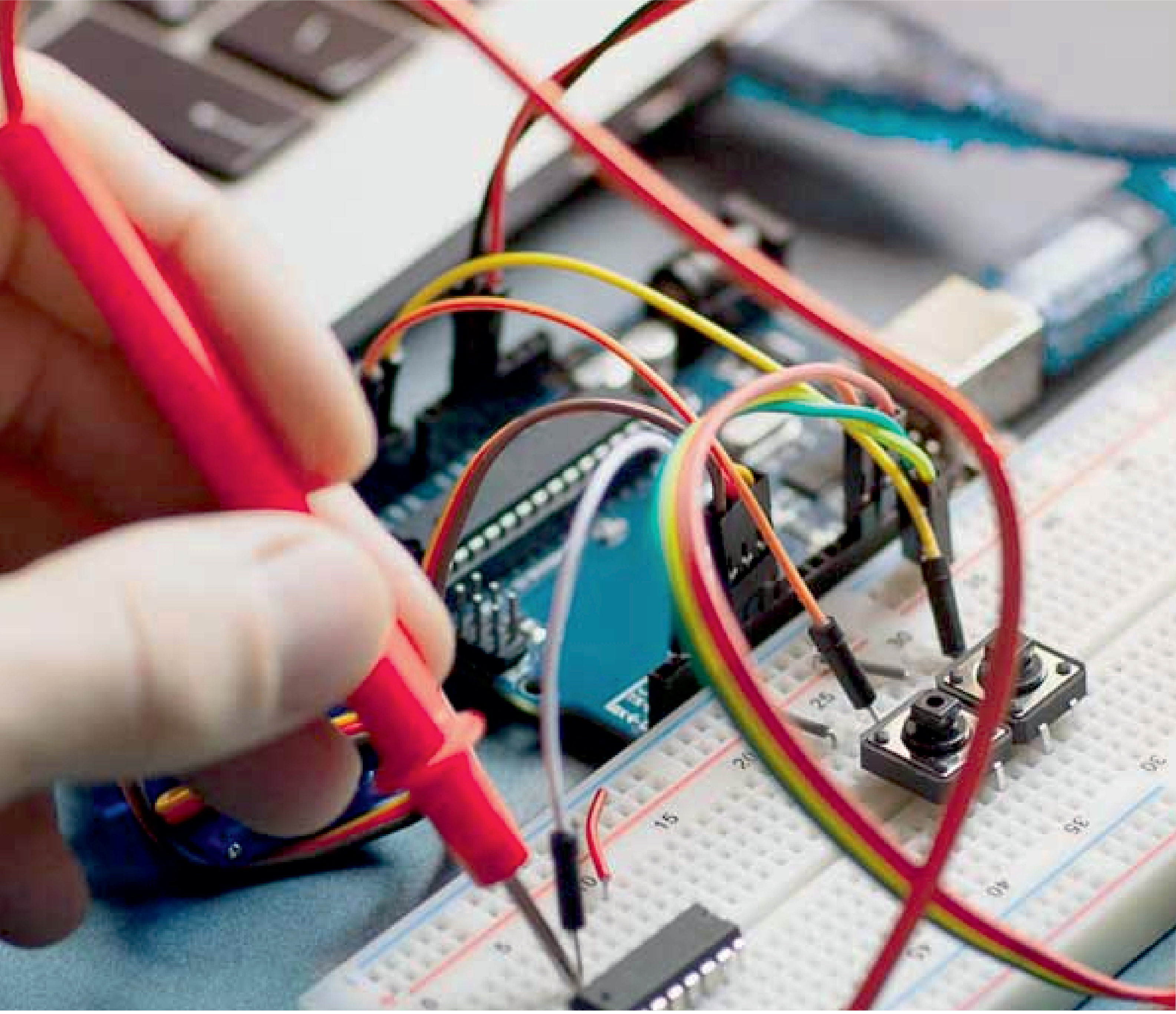

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