Performance Analysis of Channel Estimation in 5G millimeter-Wave-MIMO Heterogeneous Systems

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Abstract
Millimeter Wave (mm-Wave) - massive Multiple-Input Multiple-Output (MIMO) technology has been a subject of today’s growing interest in both industry and academia for future wireless standards and has significant potential to provide considerable gains in data rates, link reliability and Energy Efficiency (EE). Sparse recovery has great capability in Channel Estimation (CE) for mm-Wave - Massive-MIMO (Ma-MIMO) heterogeneous wireless networks and in this context; the existing better candidate “Orthogonal Matching Pursuit” (OMP) algorithm is modified for CE in such networks. This paper will provide an opportunity in setting up of such a network, and the practical observation of the effect of a change in threshold, sparsity and noise levels as well as quantity of Radio Frequency (RF) chain systems. The performance analysis of CE accuracy in terms of Normalized Mean Square Error (NMSE) verses a given Signal-to-Noise (SNR) range in dB is calculated using this modified algorithm, much better than the existing OMP methods and compared against the ideal Genie case under a wide range of noise encountered. It has been observed that in a very high noise environment, NMSE of this noise resistant algorithm is approximate (10^{0.5} to 10^{-3.5}) in low SNR range (-10 to 30) dB and approximate (10^{-1.5} to 10^{-5.5}) in high SNR range (10 to 50) dB. It comes out to be approximate (10^{-1} to more than 10^{-5}) in case of combined effect involving the reduction of quantity of RF chain systems to half and 10 times enhancement of threshold level in a very high noise environment and low SNR range.

Keywords- Compressed Sensing, Channel Estimation, Millimeter Wave, Massive Multiple-Input Multiple-Output, Sparse Signal Processing.

1. INTRODUCTION
Ma-MIMO is a prominent technology to get thousand times data rates in mm-Wave heterogeneous wireless communication systems, especially today’s smart phones. It is due to a fact that the mm-Wave band has a huge spectrum availability to solve a problem of global bandwidth shortage as well as mm-Wave wireless connections allow the quick deployment and mesh-like connectivity with cooperation between Base Stations (BSs). This
alternative enabling technique helps in achieving the high data rate and Channel Capacity (CC) by employing the high gain directional transmission for future 5G and 6G broadband wireless communication networks. It occupies a multitude of antennas at the BS to serve multiple users simultaneously as well as provides high-throughput green wireless communications as a prominent technique. It utilizes the higher degree of spatial freedom, to improve the capacity and EE of the wireless system intensively. Thus, Ma-MIMO systems are widely accepted as a distinguished enabling technology for 5G wireless networks [1] and vehicular communication systems [2]. The mm-Wave bands were initially used for indoor [3, 4] and fixed outdoor short-range Line-of-Sight (LOS) communications. Presently, mm-Wave bands ranging from (30-300) GHz are largely used for satellite communications [5] and cellular backhaul [6] – [8]. More recently, mm-Wave transmissions have provided very high throughput in case of wireless Local Area Networks, Personal Area Network systems and Wi-Fi cellular networks [9], [10] [11]–[13] in 60-GHz bands. It is due to a fact that mm-Wave spectrum makes the propagation characteristics of different mm-Wave bands much more comparable and homogeneous in nature, and it is not significantly affected by atmospheric absorption and rain attenuation characteristics. While these systems provide rates in excess of 1 Gb/s due to the spectrum severe shortage at the sub-6 GHz frequencies and the continuous rise in the demand for high data rate services, the links are typically for short-range or point-to-point LOS settings. In more concentrated deployments, the wide bandwidths of mm-Wave signals may avoid alternatively cell splitting by remarkably increasing the capacity of individual small cells. Backhaul of a suitable form is also provided in the mm-Wave spectrum between BSs to handle much greater capacity and it further reduces costs. However, the little wavelength of mm-Wave signals also makes use of proportionally greater antenna gain for the same physical antenna size, and may use polarization as well as new spatial processing techniques specifically Ma-MIMO and adaptive beamforming (BF) [14]. Hence, the higher frequencies of mm-Wave signals do not increase free space propagation loss, provided the antenna area remains intact and suitable directional transmissions are utilized to improve the link margin operation. This loss from going to the higher frequencies can be covered up from much more antenna elements keeping intact the physical antenna area. The mm-Wave systems have an omnidirectional path loss that is 20–25 dB worse than conventional microwave frequencies and short cell radii combined with highly directional beams are capable of completely compensating this loss, which increases with the denser urban environment, and, in fact, improve upon today’s systems. A related advantage of highly directional transmissions or appropriate BF is that the links are directionally isolated in nature and intercellular interference negligibly affects the performance of current small cell networks.
To attain high spectral efficiencies, an accurate channel estimate is needed, which is a cumbersome task in Ma-MIMO. The estimation problem exploits the small quantity of paths that characterize the mm-Wave channel and is solved by CS techniques effectively[16]. The basic idea given by CS theory is to retrieve a signal which is sparse in some domain from extremely small quantity of non-adaptive linear measurements by applying convex optimization. In the other way, it recovers precisely a sparse vector of high dimension by decreasing its dimension. Stated another viewpoint, the problem is capable of considering a calculation of a signal’s sparse coefficient with respect to an over-complete system [15]. The three categories of algorithms, namely greedy iterative algorithms, convex relaxation algorithms, and Bayesian inference algorithms are available to acquire the Channel State Information (CSI) analysis. The channel statics are judged by a user based on CSIT quality estimation parameter. The concept of CS under greedy iteration algorithms was essentially applied for random sensing matrices, which allow for a small amount of non-adaptive, linear measurements. Presently, the idea of CS has been generally replaced by sparse recovery [15]. According to CS theory, enough measurement vectors are required to guarantee the sparse vector retrieved with high probability. There are two differences between sparsity adaptive proposed algorithm and conventional OMP algorithm. Firstly, the proposed algorithm retrieves a sparse vector of high dimension by using structured sparsity of Ma-MIMO channels from one low dimensional vector. Secondly, it acquires the sparsity level in an adaptive manner. On the opposite end, the conventional algorithm retrieves the sparse vector without utilizing the structured sparsity and it needs prior information of correct sparsity level. Furthermore, different sub-problems of CS like sparse approximation, identification of support, and sparse identification, are explained, with respect to wireless systems.

Research challenges in front of complete integration of the Ma-MIMO system into future wireless systems are as follows:

(a) MIMO systems are impracticable for Frequency Division Duplex (FDD) systems, but can be employed in Time Division Duplex (TDD) systems because of having channel reciprocity [17]. (b) Conventional CE methods need a large pilot and feedback overhead scaling proportionally with quantity of BS transmitting antennas, and this overhead provides impracticable condition for large-scale FDD MIMO systems [17]. (c) Also, Ma-MIMO system experiences pilot contamination from adjoining cells in a case of high transmitted power; otherwise the thermal noise will affect it. Methods will be needed to combat this problem to carry
out the desired performance [17]. (d) The suitable channel models of Ma-MIMO systems are urgently needed, and failing these, various researchers will experience a difficulty to accurately validate the algorithms and techniques [17]. (e) For CE, TDD scenarios are only considered carefully for Ma-MIMO due to the expensive nature of CE and feedback. Even for TDD to work, Ma-MIMO channel calibration is urgently needed. New methods and schemes will be required for the purpose of CE in Ma-MIMO systems [17]. (f) The RF chains generate the massive amount of data and exceptionally fast processing algorithms will be needed for processing this data [17]. (g) Another challenge is to handle power consumption of various devices, which are used to support many antennas with widespread bandwidths. Sparse signal processing is important for implementing mm-Wave communication in 5G wireless networks, which is employed in this paper. (h) The transmitted signal should be adjusted according to available channel conditions, while eliminating unwanted channel characteristics in mm-Wave band.

Related work

Some CE algorithms had been proposed to efficiently regain the sparse channel matrix by using low rank and structural sparsity properties [18-19, 20-23, 24], including blind, semi-blind and pilot-aided estimation techniques. For blind and semi-blind CE techniques, the basic idea is to utilize certain inherent features in a modulated signal or exploit a decision feedback method rather than many pilots to acquire the CSI [18-19]. The accurate CSI feedback measurement from the User Equipment (UE) to BS was assumed, which is practically impossible [25]. Paulo R. B. Gomes et al. [26] formulated two tensor-based semi-blind RXs-one iterative alternating Least Squares (LS) in nature and one closed form solution for joint DL (Downlink) and UL CE. But the closed form computed Singular Value Decomposition (SVD), which was having high computational complexity. They evaluated RX’s performance in terms of the NMSE measurement between the estimated; and true DL and UL channel matrices in an mm-Wave scenario. [27] The existing algorithms OMP and VAMP (Vector Approximate Message Passing) used only the sparsity of the channel matrix, while SVT (Singular Value Thresholding) capitalized only on its low-rank property. Two-Stage estimation using both Sparsity and low Rankness (TSSR) utilized both properties by initially implementing the SVT operator to regain the channel matrix, and then used it as an input parameter to VAMP. The performance of the OMP algorithm was not well over the training length or SNR due to the discretization error of the AoA. Also, the VAMP algorithm was not capable of recovering the $64 \times 64$ MIMO channel matrix for a small
amount (<800) of training symbols. It was due to a fact that this algorithm was depending upon the calculation of the statistical information of the sparse signal, and this information could not be seized for small training length. TSSR algorithm was dependent upon successive application of SVT and VAMP algorithms, and could not retrieve the channel for small values of training length. This indicated that the independent treatment of each stage did not allow the joint utilization of the channel sparsity and low-rank properties [27].

The practical implementation of large antenna arrays, hybrid precoding, and the sparsity of mm-Wave channel prevented traditional CE methods designed for a lower-frequency MIMO system applicable for the mm-Wave -Ma-MIMO system [28]. Hence, specific CE techniques for mm-Wave-Ma-MIMO systems were proposed in [29- 33]. In [28], [30, 31], the Eigen-decomposition based algorithms using the availability of low rank channel covariance matrices were designed for CE. Unfortunately, the complex nature of these CE algorithms was high to a large extent and required large overhead to obtain reliable channel covariance matrices. To eliminate this problem, [32, 33] proposed the CS based CE methods by exploiting the sparsity of mm-Wave channel in the angular domain and incorporating the hybrid architecture, while dealing with the management of multi-cell inter-cell and multi-user intra-cell interference in ultra-dense heterogeneous networks as well as beam squint effect. But, the complexity was still of high level due to the non-linear optimization; their effectiveness highly depended on the Restricted Isometry Property (RIP) as well as estimation of the whole cosparse mm-Wave channel instead of its gain only. In [1], various propagation measurements on the mm-Wave channel at 60 GHz were applied in various outdoor environments. Angle information of the user plays a significant role in the mm-Wave massive systems to simply CE. The conventional MUSIC and ESPRIT are not acceptable for the mm-Wave communications due to the following principal reasons: 1) They were of very high-level computational complexity during SVD operation due to the large quantity of antennas; 2) They belonged to blind estimation category, which was originally conceived in detail for Radar application, and avoided the full usage of the training sequence in wireless communication systems [28].

Athar Waseem et al. [17] and Ayon Quayum et al. [34] discussed a new non-orthogonal pilot design scheme, different from conventional orthogonal pilot designs based on Nyquist sampling theorem in a single cell scenario. It is due to a fact that pilot overhead is very large due to a huge number of transmitting antennas at BS for Ma-MIMO FDD (such as OFDM) systems and did not exploit structural aspects such as sparsity, which led to poor performance. Manoj A et al. [35] discussed the three pilot-based strategies for estimating the CE in a multi-user mm-Wave communication system. These strategies were designed to avoid the spectral leakage in frequency domain because
spatial frequencies are random in nature and can acquire continuous values. Xiaohui Bi et al. [36] considered conventional CS-based CE schemes for FDD Ma-MIMO systems to exploit the temporal common sparsity of wireless channels in order to minimize the pilot overhead as well as discussed an adaptive Modified-Subspace Pursuit (M-SP) algorithm to adaptively adjust the prior channel support quality parameter to the appropriate value in the case of model mismatch. This algorithm improved the performance of CE. But it can perform well if the channel statics are correct at the Transmitter (TX) side, which is essential to capitalize the spatial multiplexing gains and array gains of Ma-MIMO. Ma-MIMO was a multi-user MIMO (MU-MIMO) system, which used spatial multiplexing over a wireless channel, and in one-bit Ma-MIMO, high-order constellations conveyed information at higher rates than with QPSK in the presence of MU interference and non-linearity [37]. It is revolved as the prominent 5G technology, which is efficient in eliminating the gap between current telecommunication standards and future requirements for 5G wireless systems. It provided the largest gains from spatial multiplexing of a lot of user’s simultaneously requesting data per cell [38].

**Problem statement**

CE is a cumbersome task in wireless communications. It is due to a fact that the transmitted signals arrive at the RX along multiple paths because of various reflections and scatterings. They add either constructively or destructively, in a case of these paths having similar delays and hence, this situation gives rise to fading. They appear as signal echoes, in a case of these paths having dissimilar delays. The channel is variable in time due to a movement of the TX, the RX, or the scattering objects. The NMSE with respect to low and high SNR regimes in dB is found out in an mm-Wave-Ma-MIMO heterogeneous wireless network, and performance analysis of quantity of RF chain systems, threshold level and sparsity level under wide range of noise encountered is carried out in this network. For it, the existing OMP algorithm in spite of its above stated limitation is modified in this paper for CE in such a network.

**Contributions of our paper**

The following steps are the novelty of this paper: (a) An mm-Wave- MIMO system is set up practically for CE using a sparse signal processing. (b) The existing OMP algorithm is modified and used for CE in the set-up system in terms of the performance parameters such as NMSE with respect to a given SNR range in dB. (c) The above designed algorithm is compared against ideal Genie case and an analysis of CE involving the effects of changes in threshold level, sparsity level and quantity of RF chain systems is performed under a wide range of noise encountered. The remaining paper is arranged as follows:
In section 2, the subsection 2.1 provides the factors affecting CE in mm-Wave - MIMO 5G heterogeneous systems. The subsections 2.2 and 2.3 respectively provide major challenges of CE and possible approaches for CE in mm-Wave- Ma-MIMO heterogeneous systems. In section 3, the system model, channel model used and the proposed methodology are explained. The simulation results and discussion are depicted in section 4. In the last, the conclusion is provided in section 5.

Notation Paragraph

**TABLE 1 PARAMETERS GUIDE USED FOR CE PRESENTED IN THIS ARTICLE**

| PARAMETERS                                                      |  |
|-----------------------------------------------------------------|---|
| Sparsity level                                                  | $L$ |
| mm-Wave channel gain                                            | $\alpha_l$ |
| Non-Conjugate Transpose operation and conjugate transpose of matrix | $(.)^T, (.)^T$ respectively |
| Complex Gaussian random vector with mean m and covariance n     | $\mathcal{C}(m, n)$ |
| Channel noise                                                   | chNoise |
| Diagonal elements of matrix                                     | $\text{diag} \{ \}$ |
| Hermitian or complex conjugate transpose operation, $H$ of matrix | $(.)^H = (\bar{X})^T$, if $X$ is any matrix |
| SNR value from 1 to length of SNR in dB                         | $i_{SNR}$ |
| Kronecker product                                               | $\otimes$ |
| Conjugate operation of matrix                                   | $\text{conj}$ |
| True channel vector value                                       | $H$ |
| Channel vector value estimated or calculated by OMP algorithm   | $H_{omp}$ |
| Frobenius norm of vector                                        | $\| \cdot \|_F$ |
| Channel vector value estimated or calculated by Genie algorithm | $H_{Genie}$ |
| Moore-Penrose pseudoinverse operation                           | $\text{pinv}$ |
2.1 Factors affecting CE in mm-Wave MIMO 5G heterogeneous systems

(a) The mm-Wave signals are extremely sensitive to deep shadowing, bringing about outages and intermittent channel quality and hence, intermittent connectivity due to much more dramatic swings in path loss from the various obstacles in the signal path(s), and these signals will have higher Doppler spreads. The human body itself can provide a (20–35) dB loss [39] and materials such as brick can weaken signals by as much as 40–80 dB [40]. The Doppler spread of over 3 KHz at 60 km/h at 60 GHz will change the channel in the order of hundreds of microseconds, which is much faster than today’s cellular systems. The beamsteering may overcome the effects of shadowing [41]. (b) Additionally, mm-Wave systems will be inherently built of small cells, resulting in the rapid changes in relative path losses and cell association. From a systems viewpoint, these results in connectivity of highly intermittent nature and rapidly adaptable communication will be urgently required. (c) mm-Wave MIMO models consist of several multi-path components reaching in clusters. Each cluster has a possibly different distribution for the power, delay and Angles of Arrival/Departure (AoA/AoD). These clusters of the path can rapidly appear and disappear due to blockage of mm-Wave signals by many materials. This has a significant impact on CE and tracking. (d) mm-Wave networks will be inherently heterogeneous. The different buildings and surfaces through reflections and scattering are providing non-LOS paths [41]. The path-LOS components produced weaker NLOS links due to more path-loss as compared to LOS links in outdoor courtyard consisting of various buildings and some trees by using mm-Wave waves at 60 GHz [42]. The channel characterization and propagation modeling was studied in case of indoor LOS and NLOS links at 28 GHz and 38 GHz using a newly designed mm-Wave path loss model depending upon distance [43]. Various measurements involving multipath time delay spread, path loss, and signal coverage were carried out for 38 GHz mm-Wave outdoor urban cellular channels capable of implementing steerable antenna architectures of different gains and beamwidths [44]. The channels under mm-Wave are correlated in nature, not Independent and Identically Distributed (I.I.D.).

2.2 Major challenges of CE in mm-Wave - Ma-MIMO heterogeneous systems

(a) The big antenna array, low SNR before BF, and the hybrid transceiver structures having one-bit ADCs pose a major challenge. To fix these problems, four kinds of CE schemes are as follows: the CS-based CE scheme, the CE scheme with the one-bit ADC at the Receiver (RX), the parametric CE scheme, and the Subspace Estimation and Decomposition (SED)-based CE scheme. Except for the third scheme, the other three kinds of schemes depend on the hybrid MIMO transceiver structure. The parametric CE scheme eliminates the assumption of the discrete AoA/
AoD compared with the first two schemes and requires the array manifold as a priori information, like the first two schemes. SED-based CE can obtain the dominated Eigen-modes rather than the entire channel for transmission in a direct manner. But the ping-pong operation between the BS and Mobile Station (MS) can produce very much noise and decay the final estimation performance, especially in mm-Wave with small SNR before BF [45]. (b) The design of the synchronization and broadcast signals utilized in the initial cell search are required as a prominent challenge for relying on highly directional transmissions in wireless cellular systems. Both BSs and mobiles have to scan over a range of angles before the detection of these signals. (c) The signal amplitude of mm-Wave channels is highly variable in nature and critically provides a challenge to their recovery over short training periods. Current CE methods utilize either the channel low-rank property in the antenna domain or its sparsity in the beamspace domain; nevertheless, they still need a considerable amount of training symbols for the satisfactory performance. Near-Optimal BF performance in mm-Wave MIMO systems employing Hybrid architectures necessitates reliable CSI knowledge. The most significant challenge in mm-Wave - Ma-MIMO system is the overheads for CSI acquisition at BS. It is evident that the knowledge of CSI at the BS acquires a high system performance. The higher frequency of the mm-Wave band provides much smaller coherence time as the channel coherence time interval is inversely proportional to the carrier frequency. Also, Ma-MIMO means that the much larger number of parameters, especially high dimensional antenna processing will be required to be tracked at the BSs for CE, and the time required for pilot sequences scales up. However, to acquire this knowledge is very challenging practically due to the much larger numbers of transceiver antenna elements and the high channel variability [27]. Hence, the heavy pilot overhead becomes the bottleneck for the mm-Wave Ma-MIMO system. The most efficient way of obtaining CSI analysis is through reciprocity that uses Uplink (UL) training pilots.

2.3 Possible approaches for CE in mm-Wave-MIMO heterogeneous systems

(a) The mm-Wave - Ma-MIMO systems are much more attractive due to the larger bandwidth and dense antenna array compared with conventional Ma-MIMO systems working at sub-3–6 GHz. However, these systems have a limitation of small SNR before BF. Furthermore, the hybrid MIMO transceiver structure stops the direct implementation of conventional CE methods proposed for conventional Ma-MIMO in mm-Wave - Ma-MIMO systems. The designing of a CE scheme having the minimized hardware cost and extra system overheads gains an importance for mm-Wave- Ma-MIMO system compatible with that in conventional Ma-MIMO system. One possible approach is the design of a suitable analog precoding/combining that can convert the CE problem in hybrid
MIMO systems to that in conventional MIMO systems. This can be perceived by the Discrete Fourier Transform (DFT) analog precoding/combining utilizing multiple time slots [45]. (b) The codebook-based CE methods have been broadly researched in many standards, including IEEE 802.15.3c (TG3c) for WPAN and IEEE 802.11.ad for WLAN, and the acquired CSI is implicit other than explicit. In addition, both the BS and the MS also complete the BF and combining after the completion of codebook-based CE design [45]. However, the codebook design limits the performance of the current CE techniques, since beam dictionaries suffer a problem of power leakage due to the discretization of the AoA/AoD. Most currently mm-Wave CSI estimation that uses both the low-rank and sparsity properties of mm-Wave MIMO channels through a two independent stages procedure (one stage per each property) was proposed [27]. (c) From the other perspective, the CS-based CE schemes firstly used for conventional Ma-MIMO systems by using the sparsity of Ma-MIMO channels can be also exploited for mm-Wave - Ma-MIMO systems with a small amount of modifications, thanks to the much sparseness of mm-Wave - Ma-MIMO channels and this paper will provide this opportunity. MIMO technology improved the CC and the SE by utilizing multipath property without any increase in the applied power [46-48]. The CE analysis of modified OMP algorithm with respect to ideal Genie case is carried out using the sparse signal processing concept in an effective manner under the different SNR ranges (dB) in this work. This work will restrict the number of antennas used due to the dominance of the mutual coupling effect, and will definitely set up the suitable guidelines regarding the CE analysis in the future 5G and 6G mm-Wave heterogeneous wireless networks.

3. SYSTEM MODEL, CHANNEL MODEL and PROPOSED METHODOLOGY

3.1 System model

The system model is depicted in fig. 1, which is highly flexible, scalable and configurable to handle large variation in requirements occurring in different scenarios and is described as follows:
Fig. 1 MIMO Architecture at mm-Wave based on hybrid analog-digital precoding system as well as combining system

A wireless heterogeneous communication network of hybrid nature operates in the mm-Wave band and consists of a $N_t$-antenna TX desiring to send $N_s$ independent parallel data streams to a $N_r$-antenna RX, where $N_s \leq \min(N_t, N_r)$. $L_t$ RF chain systems ranging from 1 to $n$ are supposed to be available in TX, where $L_t \leq N_t$ and $L_r$ RF chain systems ranging from 1 to $n$ are supposed to be available in RX, where $L_r \leq N_r$. Also, $L_t = L_r$. It must hold $N_s \leq L_t = L_r$ for accurate decoding at RX. Large-scale antenna arrays and RF front-ends consist of DAC, ADC, frequency
synthesizers and Transmit/Receive (T/R) multi-beam antenna arrays. The T/R array contains RF components like filters, mixers, power amplifiers and low noise amplifiers, each with its own set of performance specifications and corresponding test methods. TX processes the symbol vector \( s \in \mathbb{C}^{N_s \times 1} \) with a precoding matrix \( F \in \mathbb{C}^{N_t \times N_s} \) generated by a RF precoding system in a linear fashion before starting the transmission. It is assumed that \( F \) is split as \( F = F_{RF} \cup F_{BB} \); \( F_{RF} \in \mathbb{C}^{N_t \times L} \) represents the analog RF precoding matrix executed using analog phase shifters (its elements are having constant amplitude) and \( F_{BB} \in \mathbb{C}^{N_{RF} \times N_s} \) is the digital BB precoding matrix. \( F_{RF} \) and \( F_{BB} \) are designed to maximize the mutual information achieved by Gaussian signaling over the mm-Wave channel. In practical mm-Wave systems, received signals must be combined in the analog domain, and possibly in the digital domain, before any detection or decoding is performed. Any of the precoding schemes among Zero Forcing (ZF), Maximum Ratio Transmission (MRT) and Minimum MSE (MMSE) may be used depending upon their relative merits and demerits. Here the \( F_{RF} \) has the elements, which are normalized as \( |[F_{RF}]_{i,j}|^2 \leq N_t^{-1} \) with \( i = 1, 2, 3, \ldots N_t \) and \( j = 1, 2, 3, \ldots L_t \). Also, it is assumed as \( \|F^{(n)}\| \leq 1 \forall n = 1, 2, 3, \ldots N_s \). A total power constraint \( P \) is considered for TX in such a way that \( E \{ \|F P s\|^2 \} \leq P \), where \( P = \text{diagonal} \{ P_1, P_2, P_{N_s} \} \) and \( P_n \) is power assigned from TX to its \( n \)th data stream. The BB \( N_t \times 1 \) received mm-Wave signal in complex form at RX is given by the equation (3.1):

\[
y = HFP s + n
\]

where \( H \in \mathbb{C}^{N_r \times N_t} \) represents the channel gain matrix between RX and TX, and \( n \in \mathbb{C}^{N_r \times 1} \) denotes the zero-mean AWGN vector with covariance matrix \( \sigma^2 I_{N_r} \).

The channel gain matrix, \( H \) represents the complex channel gains between the antenna elements of the TX as well as of the RX. It has dimensions \( N_t \times N_r \). Each complex value in the matrix represents the magnitude as well as phase of the channel gains between one pair of TX-RX antenna elements. Only few angles, namely the AoAs and AoDs of the paths, have large energies; other angles have near zero energy due to the poor scattering nature of the mm-Wave channel, Hence, the matrix has the peak values at the positions corresponding to the AoAs and AoDs, and other angles values are near zero.

After receiving the mm-Wave signal, RX is supposed to process \( y \) with an optimum-performance filter \( W \in \mathbb{C}^{N_r \times N_t} \) in a linear fashion and obtains an approximation of transmitted symbol vector \( s \) as

\[
\hat{s} \triangleq W^H y = W^H H F \sqrt{P} s + W^H n
\]
At RX $W$ is decomposed as $W \triangleq \text{W}_{\text{RF}}\text{W}_{\text{BB}}$; where $\text{W}_{\text{RF}} \in \mathbb{C}^{N_r \times L_r}$, represents the RF combining matrix implemented similar to $F$ (its elements are having constant amplitude) and $\text{W}_{\text{BB}} \in \mathbb{C}^{L_r \times N_s}$ is the BB combining matrix. In this model, the entries of $\text{W}_{\text{RF}}$ are normalized as $[\text{W}_{\text{RF}}]_{i,j} \triangleq N_r^{-1}$ with $i = 1, 2, 3 \ldots N_r$ and $j = 1, 2, 3 \ldots L_r$. $\text{W}_{\text{RF}}$ and $\text{W}_{\text{BB}}$ minimize the MSE between the transmitted and processed received signals.

### 3.2 Channel Model

The mm-Wave has a property of the narrow shadow boundary due to a little diffraction angle. Moreover, the small wavelength results in a high path-loss as well as the limited scattering. Therefore, a small number of multi-path components are actually available between the BS and each user. A geometric channel model is used to explain such a sparse channel for a particular user [36, 49], which has become one of the research hot spots in the wireless communication system. Similar to [50], [29], [30], [31], [51] a modified geometric channel model having $L$ number of scatterers is used to evaluate the performance of practical wireless communication systems, where each scatterer plays a part in generating one propagation path commutating from the TX to RX link of certain physical distance $D$.

The mm-Wave-MIMO sparse channel is defined by the equations 3.3-3.5. $H$ is defined in the following manner under this model:

$$H = \sqrt{\frac{N_rN_c}{L}} A_T(\theta_r) \text{diag}(\text{complex } \alpha) A_R^H(\phi_l)$$  \hspace{1cm} (3.3)

where transmitting array matrix as a function of angle, $A_T(\phi_l) \in \mathbb{C}^{N_t \times L}$, with $\phi_l = [\phi_1, \phi_2 \ldots \phi_L]$ and receiving array matrix as a function of angle, $A_R(\theta_r) \in \mathbb{C}^{N_r \times L}$, with $\theta = [\theta_1, \theta_2 \ldots \theta_L]$ are described as follows:

$$A_T(\phi_l) \triangleq [a_T(\phi_1) a_T(\phi_2) a_T(\phi_3) \ldots a_T(\phi_L)]$$  \hspace{1cm} (3.4)

$$A_R(\theta_l) \triangleq [a_R(\theta_1) a_R(\theta_2) a_R(\theta_3) \ldots a_R(\theta_L)]$$  \hspace{1cm} (3.5)

and $L$ is the sparsity level.

Obviously, equations 3.3-3.5 represent a sparse channel model that shows both the properties of low rank and the spatial correlation in case of the mm-Wave-Ma-MIMO hybrid system. These equations result in the approximate quantized angle with bounded resolution. The variable $\phi_l \in [0, 2\pi]$ with $l=1, 2, \ldots L$ represents the $l$’s path of Angle of Departure (AOD) starting from TX. The variable $\theta_l \in [0, 2\pi]$ with $l=1, 2, \ldots L$ represents the $l$’s path of Angle of Arrival (AOA) ending at RX. Additionally, $a_T(\phi_l) \in \mathbb{C}^{N_t \times 1}$, $a_R(\phi_l) \in \mathbb{C}^{N_r \times 1}$ are named as the array response vectors at TX and RX, respectively (for Uniform Linear Antenna Arrays (ULAs) with antenna spacing of a half wavelength for satisfactory optimum performance). Appropriate ULA steering guarantees highly directional signal
transmission, thereby, ensuring the gains required to prevent the high path losses suffered by mm waves. It is further assumed that the amplitude of each path is mm-Wave distributed in nature. The multipath delay spread is assumed to zero for convenience, which increases with the reflective nature of the surrounding environment.

The normalized value of $F_{BB}$ is represented as:

$$\text{Normalized } F_{BB} = \sqrt{N_s \frac{F_{BB}}{\|F_{BB}\|_F}}$$

where $N_s$ is independent data streams. If channel matrix $H$ was well conditioned, the MIMO channel had higher probability for the capacity rise of MIMO system, on the other hand if $H$ was not conditioned well, the MIMO channel was correlated to a high degree and the signals propagated through MIMO channel induced huge interference as well as Bit Error Ratio (BER) [52].

### 3.3 Proposed Methodology

The conventional methods for CE are not applicable in 5G wireless networks due to more latency of the order of 200 msec and 100x lesser data rate at 100 Mbps speed as well as scarce frequency spectrum supporting up to 4000 devices per Km$^2$ while enabling higher power consumption. Hence, the proposed methodology is based on the fact that the existing OMP algorithm is modified through MATLAB simulation as explained by the mathematical equations 3.6-3.18 in a CS framework for a CE implementation in mm-Wave Ma-MIMO Heterogeneous Systems, which the other related papers of all researchers lacks. Its proposed workflow diagram is given in fig. 2. In it, the simulation parameters like number of TX/RX antennas, quantity of RF chain systems, number of beams, grid size, number of iterations and sparsity level are set up in an mm-Wave-MIMO heterogeneous wireless network. The initial data like threshold level, low and high SNR ranges, zero MSE of modified OMP CE algorithm to be used and ideal Genie case, G-quantized TX array/RX array response matrix and zero channel matrix are established. The channel matrix $H$ as given by the equation 3.6 is calculated as:

$$H = H + \frac{N_T N_R}{L} \sum_{l=1}^{L} \alpha_l A_R(\theta_l) A_T^H(\varphi_l); \quad (3.6)$$

where $N_T = 32; N_R = 32; A_R(\theta_l)$ is receiving array matrix; $A_T^H(\varphi_l)$ is the Hermitian of transmitting array matrix.

The $H$ is reshaped according to the transmitting and receiving array as:

$$H_{omp} = A_R(\text{reshape}(h\_b\_omp, N_R, N_T)) A_T^T; \quad (3.7)$$

where the “reshape” function does the reshaping of $h\_b\_omp$ as briefly described in equation 3.7 into a $N_R$ by $N_T$ array.
The function of the modified OMP algorithm is designed as:

\[ h_{b\_omp} = OMP\_mmWave\_Est(y, Qbar, omp\_thrld); \quad (3.8) \]

where function named “OMP_mmWave_Est” takes three parameters named y, Qbar and omp_thrld respectively as the input values, which are briefly defined as follows:

\[ \text{Received signal matrix } y = \sqrt{snr} Q H + ChNoise; \quad (3.9) \]

\[ snr = 10^{(\{SNR\}/10); \quad (3.10) \]

\[ Qbar = \sqrt{snr} Q (A^{\text{conj}} T \otimes A_R) \quad (3.11) \]

The sensing matrix involving the Kronecker product of mm-Wave matrices like F_RF, F_BB, W_RF and W_BB is calculated as:

\[ Q = (F_{BB}^T F_{RF}^T) \otimes (W_{BB}^T W_{RF}^T) \quad (3.12) \]

and \( omp\_thrld = 1 \) is taken as an initial stage of threshold value of the OMP algorithm.

The Kronecker product provides better performance in case of distortion, and better recovery of the low SNR bands or pixels of the multidimensional signals than independent recovery of space and time when specially combined with the wavelet basis. It also provides varying degree of smoothness between the temporal and spatial dimensions [53]. The performance analysis of the modified OMP algorithm is evaluated in wide range of noise encountered in the low and high SNR regimes and is compared with an ideal Genie case via a metric, namely, NMSE, which is calculated as:

\[ \text{MSE in case of OMP } (\hat{i}_{SNR}) = \frac{\|H_{\text{Hat}}-H_{\text{OMP}}\|_F^2}{N_T N_R}; \quad (3.13) \]

\[ \text{MSE in case of Genie } (\hat{i}_{SNR}) = \frac{\|H_{\text{Genie}}-H_{\text{Genie}}\|_F^2}{N_T N_R}; \quad (3.14) \]

where \( H_{\text{Genie}} = A_R(\text{Genie}) \text{diag}([chGainEst]) A_R^H(\text{Genie}) \quad (3.15) \]

The following equations describe the estimation of channel gain as \( chGainEst, Q\_ORACLE \) and \( kp \) as:
\( chGainEst = \text{pinv}(Q_{ORACLE}) y; \) \hspace{1cm} (3.16)

\[ Q_{ORACLE} = \sqrt{\text{snr}} Q \, kp \] \hspace{1cm} (3.17)

and \( kp = A_{conj}^T \otimes A_R \) \hspace{1cm} (3.18)

In the last, the effects of changing threshold value, quantity of RF chain systems, wide range of noise encountered and sparsity level is observed practically by calculating NMSE vs. low and high SNR ranges, which are absent in the related papers as shown in table 3.
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Start

Set up simulation parameters like number of TX/RX antennas, quantity of RF chain systems, number of beams, grid size, number of iterations and sparsity level

Set up the initial data like threshold level, SNR range, zero MSE of modified OMP CE algorithm to be designed and ideal Genie case, G-quantized TX array/RX array response matrix, zero channel matrix

For simplicity RX array response matrix = TX array response matrix. Load mmW matrices like $F_{RF}$, $F_{BB}$, $W_{RF}$ and $W_{BB}$; and calculate the sensing matrix using these matrices

Generate AoD/AoA uniformly in grid for L multipath signal components, channel gain, channel matrix for the corresponding channel gain and true AoAs/AoDs; and TX/RX array response matrix corresponding to true AoAs/AoDs

Generate the noise vector, measurement vector $y$, equivalent dictionary matrix for Compressed Sensing (CS) -problem

Perform the estimation of beamspace channel by using the modified OMP CE algorithm, error measurement; compare this estimation and error measurement with ideal Genie case

Has number of iterations reached?

NO

YES

Terminate the program

Fig. 2 Proposed Workflow Diagram
4. SIMULATION RESULTS and DISCUSSION

The results of this work have been simulated on MATLAB software. The simulation parameters as shown in two cases in tabular form 2 are as follows:

Table 2

| Case 1 | Case 2 |
|--------|--------|
| $N_t = 32; N_r = 32$; Quantity of RF chain systems = 8; Grid size = 32; Number of Beams = 24; Number of iterations = 3; Sparsity level, $L = 5$; Threshold Level = 1. Channel matrix is initialized to zero as: $H = \text{zeros} (N_r, N_t)$; Range of SNR in dB as SNRdB = [-10:10:30]; MSE of proposed modified OMP algorithm and ideal Genie case are initialized to zeros as: $\text{mseproposed} = \text{zeros} (\text{length (SNRdB)}, 1); \text{mseomp} = \text{zeros} (\text{length (SNRdB)}, 1); \text{msegene} = \text{zeros} (\text{length (SNRdB)}, 1)$ | Range of SNR in dB as SNRdB = -10:10:30, keeping all the conditions same as case 1. |

The CE method is based upon modified OMP algorithm, which detects the CSI by picking the strongest signal path in the multi-path geometric model, defined by the equations 2.3-2.5. It is based upon AoA of the received strongest signal in terms of direction of cosine by the directional antennas. The mm-Wave matrices are loaded and the proposed algorithm is designed and used after implementing the sparse signal processing due to its smallest running time as well as computational complexity among the existing OMP algorithms. Its computational complexity grows with the sparseness in a linear fashion. The channel statistics are correct at TX side and this noise resistant algorithm improves the performance of CE under the wide range of noise encountered. The noise is considered as the non-zero elements, which badly damage the sparsity of the mm-Wave channel and minimize the number of available beams.
Its high performance is attained when huge numbers of antennas are used at both source and destination. It is due to the fact that this huge number of antennas overcomes the severe path loss over the mm-Wave frequency bands and hence, extends a coverage area. The steering of these antennas provides very high directivity and CC. Another way of controlling this path loss is through the application of suitable BF method. The maximum possible array gain is achieved with the more directive i.e. less beam-width transmission in an mm-Wave environment, and both array gain and beam-width depend upon the array structure chosen. For large arrays, random gains become static. It is well assumed in the case of MIMO systems that the channels existing between transmission and reception antennas are I.I.D., which is accomplished by putting the well separated antennas. Practically, the distance among the antennas is normally small due to the size of devices and provides the correlated channel in nature. A Ma-MIMO wireless system is a MU MISO system, in which BSs contain a huge quantity of antennas as compared to quantity of user devices, each having one antenna. It is used for strengthening the transmission rate, BER [54] and user capacity with simple signal processing in 5G wireless networks. It increases the capacity by spatial multiplexing, array gain and transmitting data on parallel independent channels without incurring any cost in terms of bandwidth or power [55]. Mohamed Abdul Haleem [56] observed that the massive system simplified signal transmission vector design process and this process attained the throughput approaching the capacity. It has various other advantages such as robustness, reliability, and utilization of low-cost hardware. Among the various challenges encountered in implementing its full potential were computational complexity, efficient distributed processing algorithms, and synchronization of the antenna units [56]. Analog BF steers the ULA output using single RF chain and phase shifters. Though simple, the analog method does not provide a multiplexing facility. The traditional full-digital processing needs each antenna having a connection with one RF chain, which leads to high implementation complexity, especially for mm-Wave communication systems. In this context, the implementation of fully digital BF architectures to support the multi-stream data transmission becomes prohibitive in nature due its expensive cost, hardware constraints, and power consumption of high-resolution Analog-to-Digital Converters (ADC) and Digital-to-Analog Converters (DAC) per antenna port. Hence, cost-effective and to remove the other limitations, hybrid processing structure uses analog phase shifters having far fewer RF chains than transmitting and receiving antennas, and reduces the complexity in digital domain and maximizes the performance of the communication system. In this hybrid structure, analog RF processing is carried out, which provides high-dimensional phase-only control and low-dimensional digital BB processing is executed using a suitable microprocessor efficiently. Also, the digital precoder
manages the inter-user interference arising from both CE and data transmission, and the RF precoder controls the phase and hence, improves the signal power. The precoding is mostly used transmission technique. The spatial structure of the channel is more important, because it leads to diversity, multiplexing, and BF possibilities. In [21], the angular spreads over the AoA and AoD were taken into account in the channel modeling, while the low-rank structure of the channel was utilized to minimize the number of samples required to recover the mm-Wave channel. The grids are mostly rectangular in shape and ensure the efficient communication links in mm-Wave frequencies.

The typical representation of the greedy iterative is the OMP algorithm, which is being modified here to work in an mm-Wave environment. Its main idea is based upon finding the most relevant column present in the measurement matrix to the residue in the $i^{th}$ iteration [57]. For such kinds of algorithms, a suitable criterion to finish the procedure is significant. If the sparseness of mm-Wave channel is known to a researcher in an advance manner, the algorithms will be ended when the number of iterations attains the sparsity level; otherwise, the maximum iteration number will be set larger than the real channel sparseness to guarantee the recovery accuracy. But, with regard to the proposed algorithm, an extra threshold is used to be exceeded. Threshold is chosen depending on the operating SNR and the number of measurements used. The main limitation of greedy iteration algorithms is that they cannot prevent the quantification error of angle even when the uniform grid of angle quantization is large enough. This quantization error plays a decisive role in the high SNR range especially. This shows that the performance based on such algorithms is similar in nature because the quantification error of angle is a bottleneck for such a sparsity CE problem. Although the real AoA and AoD are replaced by discrete grid angle and the performance is lost a lot, the computational complexity is relatively smaller than convex relaxation algorithms. This is due to the fact that such algorithms do not have the complicated matrix operations such as derivation. Therefore, these algorithms are good candidates to solve such a sparse CE problem and the low delay requirement can be satisfied well for next wireless communication systems. The Genie added LS algorithm is a performance upper-bound scenario. It assumes the correct knowledge of channel support with some Genie aid and can be applied directly to retrieve the channel coefficients based on this support. However, this algorithm does not work well in case of fast varying CE due to the large Doppler shift arising from high speed railways [58]. The channel noise is varied and the NMSE of all algorithms is analyzed. The extra noise is treated as the TX’s hardware impairment and it plays a significant role at the high SNR range. It is observed that simply increasing the transmission power will increase the hardware impairments. Hence, both estimation and compensation are required urgently for a practical mm-Wave - Ma-MIMO.
system to combat them. Typically, the number of paths or sub-paths is small in mm-Wave systems. The number of iterations is a trade-off between L and the noise level, and indicates the number of detected paths. It is advised to estimate all L paths on one side, and noise does not detect small-power paths on the other side; hence, it is better not to estimate all of them. Particularly, fact used is that the mm-Wave channel consists of a small quantity of paths with respect to the typically large number of T/R antennas. The NMSE parameter is used here to measure the accuracy of different estimated methods, and CE accuracy also depends upon the number of resolvable paths, the received SNR, quantization error in angle domain, the number of pilot symbols, computational complexity and hardware impairments. The system is simulated as depicted in fig. 1. The channel model having a correlated multi-path slowly varying and narrowband mm-Wave channel is incorporated using the equations 3.3 to 3.5. The sparse signal processing in the MIMO-mm-Wave heterogeneous network is implemented as per the workflow diagram as depicted in subsection 3.3. The NMSE of proposed algorithm and ideal Genie case are calculated using the equations using the equations 3.13-3.18.
### Table 3 Comparison of CE results of various researchers and our paper

| Paper/Author(s) | Type of Model used | Essential Simulation Conditions used | Parameters measured by various researchers | Results of the proposed work (NMSE of CE) | Salient Remarks |
|-----------------|--------------------|-------------------------------------|------------------------------------------|----------------------------------------|----------------|
| [50]/Ahmed Alkhateeb et al. (2013) | mm-Wave cellular BS-MS transceiver system | $N_{BS} = 64$; $N_{RF} = 10$; $N_{MS} = 32$; $N_{RF}=6$; The ULA antenna arrays having spacing $= \frac{\lambda}{2}$; Quantized phases assumed in RF phase shifters; No. of paths $= 3$; $K = 2$ BF vectors; No. of grid points, $N = 96$ | Not considered | (0 to1) vs. rate threshold (5 to 40), when Hybrid precoding—Estimated Channel – With interference existed | Not considered; | 1. The modified OMP algorithm has in built noise handling capability and it is working both in a very high and a very low noise environments. Approx. $(10^{0.5}$ to $10^{-3.5})$ in low SNR range (-10 to 30) dB and a very high noise environment as shown in figs. 3 and 4; approx. $(10^{-1.5}$ to $10^{-5.5})$ in high SNR range (10 to 50) dB and a very high noise environment as shown in figs. 5 and 6; approx. $(10^{-1}$ to more than $10^{-5})$ in case of both $N_{RF} = 4$ (half), $omp_{\_threshold} = 10$ times increased in a |
| [31] Jiguang He et al. (2014) | mm-Wave-MIMO hybrid precoding/combining and channel tracking system | $N_t =N_r = 64$ with $N_{RF} = 4$; $d = \lambda/2$ and $L = 4$ | Not considered | Not considered | Not considered | 2. It has DOA 0.9375 in terms of dirCos of the significant received signal components according to 32 grid points. |
| [61]/Yiying Zhang et al. (2017) | (Power Line Communication) PLC CE model | Channel bandwidth,$B_c = 30$ MHz; Sampling frequency, $f_s = 60$ MHz; Sampling time = 10 µs | MSE (0.035 to 0) (of OMP vs.SNR (5 to 30) dB | Not considered | Not considered | |
| [16] Hossein Soleimani et al. (2018) | mm-Wave-MIMO narrowband communication system with $N_t$ antennas at the TX and $N_r$ antennas at the RX | Average channel gain=0 dB; $N_r = 32$; $N_t = 4$; ULA | MSE (-20 to more than -22) dB of OMP vs. DFT size multiple (1 to 4); MSE approx. (-24 to -26) dB of AGDAR vs. DFT size multiple (1 to 4) at SNR=20 dB | Not considered | Not considered; | 3. It is better |
| Reference | System Description | Channel Model | Antenna Configuration | SNR Comparison | Complexity Comparison |
|-----------|--------------------|---------------|-----------------------|----------------|-----------------------|
| [18] Amine Mezghani et al. (2018) | mm-Wave- Ma-MIMO sparse scattering | $N_r = 32$; No. of single-antenna users, $K = 2$; $L = 3$; coherence length, $T = 1000$; Pilot sequence length, $T_p = 10$. Differential QPSK overcomed the phaseambiguity in the blind approach while standard QPSK was used for the pilot-based approach | Not considered | (approx. $10^{-1}$ to more than $10^{-2.5}$) in uncoded case of Blind, sparsity-base d proposed Algorithm vs. SNR (-15 to -7) dB per antenna | Not considered very high noise environment as shown in fig. 7, the same previous NMSE range is obtained in fig. 11 while keeping only the initial value of $N_{RF} = 8$ and $omp_{thresh} = 10$ times increased in a very high noise environment, (less than $10^{-2}$ to approx. $10^{-6}$) in a very less noise environment as shown in fig. 13, all in low SNR range (-10 to 30) dB than the existing OMP algorithms within same low SNR range; equal to $10^2$ close to BCS-LSE algorithm within same low SNR range; but much better than iterative IR based Super-Resolution CE (ULA) algorithm under NLoS channel conditions in low and high regimes, and (more than $10^{-2.5}$ to less than $10^{-4.5}$) vs. SNR (-5 to 20) dB with the threshold increased to 10 (10 times). |
| [19] Jianwen Zhang et al. (2018) | mm-Wave-MIMO sparse channel | $N = 64$: degree of freedom of system, $K = 8$, Channel coherence time, $T = 50$; and Channel sparsity level, $\rho = 0.2$ | NMSE of H approx. (0 to -50) dB vs. SNR (0 to 50) dB of proposed projection-based blind detection bilinear generalized AMP | Not considered | Not considered |
| [20] Chen Hu et al. (2018) | Hybrid-precoding mm-Wave- Ma-MIMO with arbitrary array geometry | $L = 3$; $d = \lambda/2$; $N_r = N_t = 64$; $N_{RF} = N_{RF} = 4$; Gaussian path gains assumed | NMSE approx. (less than $10^{-1}$ to approx. $10^{-1.5}$ ) vs. SNR (-5 to 20) dB of OMP; NMSE approx. (less than $10^{-1}$ to $10^{-4.5}$ ) vs. SNR (-5 to 20) dB of IR -Based Super-Resolution CE algorithm | Not considered | Not considered |
| [21] Xingjian Li et al. (2018) | point-to-point UL mm-Wave-MIMO system | $N_{RF}=N_{RS}=64$: The distance between neighboring antenna elements assumed = $\lambda/2$ of the signal. The mm-Wave channel assumed to follow the geometric channel model with $L = 2$ clusters; AoA/AoD domains discretized into 64 grid points | NMSE more than $(10^0$ to $10^1$) vs. SNR (0 to 30) dB of two stage CS (multi-beam coding); NMSE (more than $10^0$ to less than $10^{-2}$) vs. SNR (0 to 30) dB of two stage CS (random- coding) | Not considered | Not considered |

Not considered
| Reference | System Description | Parameters | Metric | Performance | Comparison | Notes |
|-----------|--------------------|------------|--------|-------------|------------|-------|
| [59] Cheng-Rung Tsai et al. (2018) | Limited scattering mm-Wave channel model | $N_{BS} = 64; N_{UE} = 16; L_{AOA} = 6; L_{AOA} = 8; M_{BS} = 24; G_{T} = 1024; G_{R} = 256$. Tunable factor of the stopping threshold for the termination condition, $c = 5$; **Threshold used in the channel subspace estimation** = 0.01 | NMSE | (-3 to 15) dB of the estimated CSI in SMV-OMP vs. received SNR (4 to 20) dB; NMSE (-7 to -19) dB of the estimated CSI in a MMV-SOMP vs. received SNR (4 to 20) dB; NMSE (-6 to -19.5) dB of the estimated CSI in MMV-subspace SM-OMP vs. received SNR (4 to 20) dB | Not considered | |
| [23] Yue Wu et al. (2018) | Hybrid point-to-point mm-Wave-MIMO communication system | $N_{t} = 8; N_{r} = 32; N_{RF} = 12; L = 2$ | Average NMSE | (Less than 10^{-0.5} to less than 10^{-2.5}) of BCS-LSE vs. SNR$_{a}$ (-10 to 15) dB at SNR$_{a}$, SNR$_{e}$=12dB; Average NMSE (10^{0} to more than 10^{-1}) of OMP vs. SNR$_{a}$ (-10 to 15) dB at SNR$_{a}$, SNR$_{e}$ = 12dB | Not considered | |
| [24] Xingbo Lu et al. (2019) | Hybrid point-to-point mm-Wave-MIMO system | $L = 5; G = 32; pilot symbol frames = 40; hardware impairment = 13 dB; N_{t} = N_{r} = 16; N_{RF}^{e} = N_{RF}^{T} = 4$ | NMSE of estimated CSI | (10 to less than -5) vs. SNR (-15 to 20 dB) of OMP algorithm with hardware impairment | Not considered | |
| [17] Athar Waseem et al. (2019) | Ma-MIMO - OFDM system | $N_{t} = 128; N_{r} = 16$ in one subgroup; **Number of antennas groups** = 8 | NMSE | (0.3 to less than 0.2) of OMP; NMSE of (0.2 to 0.05) of SUCoSaMP algorithm | Not considered | |

5. The proposed work has considered the importance of the performance analysis of CE accuracy as a function of change in threshold, sparsity and noise levels as well as quantity of RF chain systems as well as simulated, analyzed and evaluated the system model to prove the effectiveness, which have been depicted in the ‘results of proposed work’ column in this table and simulation results i.e. figures 3-13.
| Reference | System Description | Parameters | Evaluation Criteria | Comparison |
|-----------|--------------------|------------|---------------------|------------|
| [60] Wei Xu et al. (2019) | Ma-MIMO - OFDM system | $N_r = (48, 64)$; The number of OFDM subcarriers, $F = 256$; $P = 16$; CP length of transmitted OFDM symbols = 64; Length of assumed Rayleigh channel = 60; Modulation = 16 QAM | MSE (less than $10^{-1}$ to less than $10^{-3}$) of SMV-OMP for $N_r = 48$; MSE (more than $10^{-1}$ to approx. $10^{-3.5}$) of SMV-OMP for $N_r = 64$, all vs. SNR (0 to 20) dB | Not considered | Not considered | Not considered |
| [62] Biao Wang et al. (2019) | OFDM system | $F = 256$; No. of pilot frequencies/OFDM symbol = 32; Random pilot insertion, Channel length = 60 | NMSE (less than $10^{0}$ to less than $10^{-3}$) of OMP; NMSE approx. ($10^{0.5}$ to $10^{-2.5}$) of SOMP; NMSE approx. ($10^{0.5}$ to $10^{-3}$) of improved SOMP; all vs. SNR (5 to 30) dB | Not considered | Not considered | Not considered |
| [25] Imran Khan et al. (2019) | 5G FDD multiuser Ma-MIMO systems | $N_{BS} = 128$; $N_{UE} = (2-12)$; $N_{user} = (5 - 30)$; Channel sparsity = 15; Interchannel common sparsity = 6; SNR = (5 - 30) dB; $N_{pilot} = (30 - 70)$; Channel model = Narrowband flat block fading; no. of feedback bits = (1 – 8) | NMSE ($10^{0}$ to less than $10^{4}$) of MMV-OMP; NMSE approx. ($10^{0.5}$ to $10^{4}$) of Optimal Blocked –OMP (OB-OMP); NMSE (more than $10^{-1}$ to more than $10^{-3}$) of Joint – OMP (J-OMP); NMSE($10^{-1}$ to less than $10^{-3.5}$) of Modified-JOMP (M-JOMP), all vs. SNR (5 to 30) dB | Not considered | Not considered | Not considered |
Table 3 shows that the results of our proposed work are better than the existing OMP methods. The paper [50] was limited to a single - user mm-Wave system setting. The mm-Wave channels with random blockage between the BS and MS was not considered. The efficient algorithms that adaptively estimate the channel with random or TV array manifolds was not developed for mm-Wave systems. The maximum Doppler frequency $f_D = 200 \, \text{Hz}$ was considered in paper [31]. The hardware requirements were reduced by the presented method in PLC CE model [61]. In paper [16], two OMP methods namely Single Peak Cancelation (SPC) and Joint Peak Cancelation Methods (JPC) OMP methods as well as Accelerated Gradient Descent with Adaptive Restart (AGDAR) were used w.r.t. DFT size multiple (1,4). In this paper, the channel tracking technique presented was applicable for slow channel variations. The presented method was robust to statistical properties of the data and channels [18]. In paper [19], the NMSE of sparse representation of $H$ was calculated on dB scale using projection-based blind detection bilinear generalized Approximate Message Passing (AMP) algorithm. The influence of the channel sparsity on the fundamental performance limit of the MaMIMO system was also explored. In paper [20], CE was done according to AoAs/AoDs estimation and all path gains using Iterative Reweight (IR)-based Super-Resolution CE algorithm in a ULA antenna under NLOS channel conditions. The particular path was removed if its gain in (i+1) iteration was less than the pruning threshold. This process continued for all path gains and stopped if Frobenius norm of error in path gain in two consecutive iterations was less than the termination threshold.

$$N_t = N_r = 64 \, \text{ (Double in number),}$$
\( N_{RF}^R = N_{RF}^T = 4 \) (Half in number). The super-resolution CE techniques having high mobility and minimum complexity were not covered.

In paper [21], Compressed Sensing (multi-beam coding and random-coding) were utilized and in addition to sparsity, mm-Wave channels exhibited angular spreads or step sizes over the AoA, AoD and elevation domains. In this paper, these angular spreads gave rise to a useful low-rank structure, and these angular spreads along with the sparseness were simultaneously utilized to minimize the sample complexity to successful recover the mm-Wave channel. The angular spread over AoA domain was consequence of rays coming from a common AoD. The product of Hermittan transpose of precoder matrix, channel matrix and combiner matrix gave low rank matrix \( Y \) and this was recovered by its minimization / its Frobenius norm in error less than a certain error tolerance parameter over all paths. Considering this, \( H \) was estimated by its minimization of Frobenius norm between \( Y \) and the directly observed data, and this minimization was less than a certain error tolerance parameter.

\( N_{BS} = N_{MS} = 64 \) (Double in number) and double grid points were used.

Assumed \( z(t) \) and \( f(t) \) were randomly chosen from pre-determined BF/combining codebooks \( Z \) and \( F \) respectively, where the cardinality of two sets was \( |Z| = N_Z \) and \( |F| = N_F \). No beam pair was used during the sampling process. In obtaining the results,

\[ \begin{align*}
N_Z = N_F = 24, \quad T = 0.5N_ZN_F, \quad \text{AoA spread} = 15^\circ \text{ and AoD spread} = 10^\circ.
\end{align*} \]

In paper [24], the three categories of algorithms are common methods and it is possible to extend this work to other sparse signal recovery problems. In paper [59], the NMSE in terms of dB of the estimated CSI by Single Measurement Vector (SMV) - OMP, Multiple Measurement Vector (MMV) - Simultaneous (SOMP), MMV - subspace M – OMP and MMV - Channel Subspace Matching Pursuit (CSMP) methods. The proposed CS-based CSI acquisition technique to minimize the training and computational overhead for wideband frequency selective CE can be further explored. In paper [23], SNR\(_n\) and SNR\(_e\) were defined by certain formulas, and average NMSE was measured by Bayesian Compressive Sensing-Least Square Estimation (BCS-LSE) and OMP algorithms. In paper
proposed Sparsity Update Compressive Sampling Matching Pursuit (SUCoSaMP) algorithm was used in OFDM symbol transmitted by each antenna in the mentioned antenna sub-group. In paper [33], subcarrier grouping-based analysis cosparse recovery namely Reweighed Structured Analysis Cosparsity Update Subspace Pursuit (ReCoSUSP) algorithm was used for CE in wideband mm-Wave-MIMO output system. The paper [25] can be extended by incorporating mm-Wave with Ma-MIMO and performing the analysis of beamspace CE using the CS technique.

![MSE vs SNRdB](image.png)

**Fig.3** Very high channel gain and low SNR range in a very high noise environment

Figs. 3 and 4 are same in low SNR range and channel gain has no effect on the channel estimation accuracy. From figs. 3 and 4, it is observed that as SNR is varied over (-10 to 30) dB, the NMSE of the modified algorithm is changing from approx. ($10^{0.5}$ to $10^{-3.5}$) in a very high noise environment.
Fig. 4 Low channel gain and low SNR range in a very high noise environment

Fig. 5 Very high channel gain and high SNR range in a very high noise environment
Figs. 5 and 6 are same in high SNR range and channel gain has no effect on the channel estimation accuracy. From figs.5 and 6, it is observed that as SNR is varied over (10 to 50) dB, the NMSE of the modified algorithm is changing from approx. $(10^{-1.5} \text{ to } 10^{-5.5})$ in a very high noise environment. A high SNR value in figs. 5 and 6 associated with LOS component imply a low degree of scattering and provides more accuracy in steady-state behavior in CE.

![MSE vs SNRdB](image)

**Fig.6** Low channel gain and high SNR range in a very high noise environment
Fig. 7 Low channel gain, low SNR range, quantity of RF chain systems is decreased to 4 and threshold level of the modified OMP algorithm is increased to 10 from 1 in a very high noise environment.

From fig. 7, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are reduced to 4 (half) from the initial value of 8 and threshold level of the algorithm is increased to 10 (10 times) from the initial value of 1; the NMSE of the modified algorithm is changing from approx. \((10^{0.5} \text{ to } 10^{-3.5})\) in a very high noise environment and is more close to curve of ideal Genie case. The implementation cost of the mm-Wave-MIMO heterogeneous wireless network reduces by decreasing the quantity of RF chain systems in figs. 7 and 9, and an opposite situation occurs by increasing the quantity of RF chain systems to 12 from the initial value of 8 in fig. 8.

From fig. 8, it is noted that as SNR is varied over (-10 to 30) dB, the NMSE of the modified algorithm is changing from approx. \((10^{0.5} \text{ to } 10^{-3.5})\) in a very high noise environment, same as shown in fig. 4.
Fig. 8 Low channel gain, low SNR range and quantity of RF chain systems is increased to 12 from 8 in a very high noise environment

Fig. 9 Low channel gain, low SNR range and quantity of RF chain systems is decreased to 4 from 8 in a very high noise environment
From fig.9, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are reduced to 4 (half) from the initial value of 8; the NMSE of the modified algorithm is changing from approx. (10^{0.5} to 10^{-3.5}) in a very high noise environment, same as shown in fig. 4. In figs. 8, 9 and 10, the threshold level of the OMP algorithm is kept at an initial value of 1.

Fig.10 Low channel gain, low SNR range and quantity of RF chain systems is decreased to 1 from 8 in a very high noise environment

From fig.10, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are reduced to 1 from the initial value of 8; the NMSE of the modified algorithm is changing from approx. (10^{0.5} to 10^{-3.5}) in a very high noise environment, same as shown in fig. 4. It shows that the NMSE of modified algorithm is independent by a change in the quantity of RF chain systems and hence, the mm-Wave channel is being estimated properly even with one RF chain system.
Fig. 11 Low channel gain, low SNR range, threshold level of the modified OMP algorithm is increased to 10 from 1 and quantity of RF chain systems having initial value of 8 in a very high noise environment.

From fig.11, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are kept at an initial value of 8 and the threshold level of the modified algorithm is increased to 10 (10 times) from an initial value of 1; the NMSE of the modified algorithm is changing from \((10^1 \text{ to more than } 10^{-5})\) in a very high noise environment. By increasing the threshold level, the selection of very weak channel coefficients and hence, the very weak scattered received signal components may get reduce. The result is that CE mainly depends on the LOS and near-LOS signal components, and its value acquires the more steady-state behaviour. The threshold level is selected according to available SNR and channel characteristics and it will decide the effect of noise suppression. If it is very low, it fails to detect the low energy signal paths from the available noise level, and if it is adjusted properly, it well separates the available signal paths from the present noise level and will help in getting the better BER performance in mm-Wave-MIMO wireless networks.
From fig.12, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are kept an initial value of 8, the threshold level of the modified algorithm is also kept at an initial value of 1 and the sparsity level is reduced to 2 from an initial value of 5; the NMSE of the modified algorithm is changing from approx. ($10^{-5}$ to more than $10^{-3.5}$) in a very high noise environment. This curve is same as obtained in figs. 3 and 4 and reducing the sparsity level does not bring an effect, however, mm-Wave signal is already sparser in nature. It is due to a fact that the channel value is largely decided by the main LOS signal component, which remains same while reducing the sparsity level. Different sparsity levels only provide different behaviours with respect to the convergence and steady-state CE behaviour. For simplicity, the delay and Doppler shift in each propagation path are neglected in obtaining the figs. 3-13. The Basis Expansion Model (BEM) is mainly used for time-varying channel approximation.
From Fig. 3-13, it is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are kept an initial value of 8, the threshold level of the modified algorithm is also kept at an initial value of 1 and the sparsity level is kept at an initial value of 5; the NMSE of the modified algorithm is changing from (less than $10^{-2}$ to $10^{-6}$) in a very less noise environment. This curve is compared with fig. 4 and the value of the NMSE parameter is reduced further here. The noise encountered is a function of number of various TX and RX antennas involved, insufficient power supply filtering and various other factors. Therefore, the number of various antennas involved than a desired limit will increase the noise level, which degrades the sensitivity of a RX system. The TX’s hardware impairments are an additional source of noise, which increases with the transmitted power. Therefore, a compensatory circuit is urgently required in a practical Ma-MIMO-mm-Wave heterogeneous wireless system to combat them.

**Salient Features of Simulation Results:**

(a) The NMSE parameter of the CE accuracy of the modified algorithm increases with a SNR range in all figs. 3-13, but it always above the NMSE curve of ideal Genie case.

(b) In all simulation cases, the number of each transmitting and receiving antennas is fixed at 32. This is due to a fact that the significant effect of mutual coupling will reduce the correlation between the antennas will provide an additional power penalty when two antennas are placed very closely. Moreover, well separated
antennas result in a channel having little correlation. (c) The NMSE parameter is independent of the mm-Wave channel gain and sparsity level as shown in figs. 3-6 and 12. (d) The measurement of NMSE parameter is possible with one RF chain only as shown in fig. 10. (e) As the threshold level is increased to 10 times from its initial value, the NMSE parameter value is decreased further as shown in fig. 11.(f) The modified algorithm is working well in a very high noise environment as shown in figs. 3-12. (g) As the noise level is decreased to a much higher level, the NMSE parameter value is also decreased further as shown in fig. 13 and hence, CE accuracy increases further.

5. CONCLUSION
An accurate CE plays a significant role to realize the designs of hybrid precoding matrix to have a full advantage of BF gains in mm-Wave-MIMO heterogeneous systems. It is required for proper transmit BF. The mm-Wave channel can be reconstructed from the known channel statics and results in a high data rate and a high SE. However, the mm-Wave-MIMO channel contains a little quantity of dominant clusters of paths and a limited set of parameters characterizes the entire channel even with many antennas. This induces sparsity in the mm-Wave channel matrix. Deploying more antennas at BS is very much effective in improving the probability of spotting the pilot spoofing attack in Ma-MIMO systems. The working in an mm-Wave environment results in the reduced antenna size, and provides the high data rates, which assist high quality multimedia with lower delays and sustained connectivity of wireless devices. The use of other array structures like uniform rectangular planar array, elliptical, hexagonal, circular etc. is an interesting future research direction for enhancing the signal reception at mm-Wave frequencies. The throughput performance of 5G wireless communication systems on railways need to be explored in various scenarios. The convergence and feasibility issues will be explored in the improved wideband mm-Wave-MIMO CE CS-based approach involving the large grid sizes. The efficiency in compression sensing may be improved as a future research by a suitable algorithm [61].The decentralized MMSE estimation of a general correlated random vector in a mmWave - Ma-MIMO framework as a future research may be considered [63].The mmWave -based wideband collaborative spectrum sensing using a Decision Fusion Centre equipped with multiple receive antennas in case of Ma-MIMO and a ‘virtual’ Ma- MIMO based radio networks may perform in future for better sensing performance, in mitigating severe shadowing effects considerably, and in presence of correlated measurements [64]. The Ma-MIMO - mm-Wave heterogeneous system may be combined with a small cell network, and a good trade-off may be carried out for better performance in a more secure and cooperative Internet-of-Things (IOT) implementation.
in several areas as a future work [65, 66]. The novelty of the work is that the NMSE of mm-Wave-MIMO CE by the modified OMP algorithm and ideal Genie case is calculated and compared in low and high SNR ranges in a very high noise environment; and the effects of changing quantity of RF chain systems, threshold level, sparsity level in a very high noise environment, and noise level are practically observed in low SNR range only in both algorithms. It is observed that as SNR is varied over (-10 to 30) dB, quantity of RF chain systems are reduced to 4 (half) from the initial value of 8 and threshold level of the algorithm is increased to 10 (10 times) from the initial value of 1; the NMSE of the modified algorithm is decreased further, hence, increasing the accuracy of CE and follows closely to the curve of ideal Genie case as shown in fig. 7. The CE accuracy remains unaffected by the changes carried out in mm-Wave channel gain, sparsity level and quantity of RF chains systems as shown in figs. 3-6, 12, and 8-10.

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