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Massive MIMO systems for 5G: A systematic mapping study on antenna design challenges and channel estimation open issues

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Abstract

The next generation of mobile networks (5G) is expected to achieve high data rates, reduce latency, as well as improve the spectral and energy efficiency of wireless communication systems. Several technologies are being explored to be used in 5G systems. One of the main promising technologies that is seen to be the enabler of 5G is massive multiple-input multiple-output (mMIMO) systems. Numerous studies have indicated the utility of mMIMO in upcoming wireless networks. However, there are several challenges that needs to be unravelled. In this paper, the latest progress of research on challenges in mMIMO systems is tracked, in the context of mutual coupling, antenna selection, pilot contamination and feedback overhead. The results of a systematic mapping study performed on 63 selected primary studies, published between the year 2017 till the second quarter of 2020, are presented. The main objective of this secondary study is to identify the challenges regarding antenna design and channel estimation, give an overview on the state-of-the-art solutions proposed in the literature, and finally, discuss emerging open research issues that need to be considered before the implementation of mMIMO systems in 5G networks.

1 | INTRODUCTION

The next-generation of mobile networks, also known as the fifth-generation (5G) is foreseen to deliver a solution for bandwidth-hungry application, due to the dramatic increase in traffic demand of users. 5G aims to meet much higher data rates with fast connectivity, more robust reliability, spectral efficiency (SE) and energy efficiency (EE) [1]. However, there are technical requirements and challenging issues that 5G needs to overcome so that it can be implementable. One of the major challenges is that the new generation must support much higher data rate (approximately 1000✕ compared to legacy networks), which makes it essential to go to higher frequencies, 30–300 GHz (Mm-Wave) spectrum, to allow more bandwidth. The use of the mm-wave spectrum requires the use of many antennas allowing more throughput gain in the spatial dimension to overcome high path loss. Furthermore, smaller cells provided by the use of these many antenna are needed to avoid interference [2].

Recently, massive multiple-input multiple-output (mMIMO) has become the most promising wireless technology and the

main key for moving toward 5G. In mMIMO systems, the base station (BS) is deployed by using hundreds of antenna elements. The deployment of such massive number of antennas provides significant enhancement to system performance (i.e., system capacity, link robustness, energy efficiency and spectrum efficiency) [3]. For a BS having an array of many active antennas, it will be possible to communicate with the user-equipment (UE), on the same time-frequency resource by spatial multiplexing [4]. Furthermore, by upgrading the BS hardware with this massive number of antennas instead of deploying new BS sites, reduction of required transmission energy can be possible by using the beam-forming gain techniques developed for these mMIMO systems [5]. Additionally, mMIMO can improve SE by controlling the available space resources using the excess degrees of freedom (DoF) resulting from using large size antenna array elements [2].

Although the potential of using mMIMO systems is exciting, the challenges that these systems will face in march toward the next-generation of mobile networks era are enormous and hardly understood. The major challenges related to antenna design and channel estimations in 5G mMIMO systems are

mutual coupling effect, antenna selection in large antenna arrays, pilot contamination in time division duplex (TDD) systems, and feedback overhead in frequency division duplex (FDD) systems.

Detailed theoretical explanation of the mentioned challenges and open research issues along with state-of-the-art solutions overcoming some of these challenges are given in this study.

In light of those challenges, this paper can indeed be very useful for researchers who try to use mMIMO systems for 5G. To the best of the authors' knowledge, there has not been a systematic mapping study of research on antenna design and channel estimation challenges regarding mMIMO implementation in 5G systems that would allow to review the maturity in general and identify research gaps, trends, and future directions.

Throughout the systematic mapping study, 63 primary studies (among 105 primary and secondary studies) from the year 2017 to the second quarter of 2020 were selected. Afterward, we introduced a classification framework to compare the state-of-the-art approaches given in the literature. Finally, we discussed the emerging challenges and research open issues that need to be considered in future mMIMO systems approaches for 5G.

The remainder of this paper is structured as follows: Section 2 describes background literature explaining the mentioned challenges. Section 3 identifies the main research questions. The research methodology is described in Section 4. In Section 5, the analysis of the mapping study and discussion of the findings are presented. Future challenges and research directions are given in Section 6. Finally, in Section 7, the conclusion is presented.

2 | BACKGROUND

Despite having huge benefits, there are major issues that must be resolved for mMIMO before the implementation of such systems is possible for 5G. Theoretical background related to antenna design challenges and channel estimation issues are discussed in this section of the paper.

2.1 | Massive antenna array design challenges

In 5G systems, high directivity is a necessity, which can be achieved through the implementation of massive antenna arrays. The main motivation behind mMIMO is to be able to construct a massive number of antenna arrays, while controlling its pattern, for long distance communication over mmWave spectrum. The distance separating the antenna elements, and the excitation amplitude and phase of these different elements, along with the array configuration are the main parameters effecting the pattern control in mMIMO antenna arrays. A more advanced design for antenna array consists of using phased arrays. Using this method, the radiation pattern in a desired direction is maximized by designing the feeding mechanism in a way that different antenna elements use different relative phases [6].

Although the use of massive antenna arrays in mMIMO systems brings many advantages, especially in enhancing the per-

formance of communication systems in 5G, the use of a massive number of antenna comes with several challenges that need to be taken into consideration.

Different types of antenna array configurations (i.e. planar, circular and cylindrical array), result in different channel characteristics, and thus will have a huge impact on the overall performance of the system. General configuration of array systems at the BS, such as planar and circular configuration exhibit a huge deficiency, where the beam can only be adjusted in the horizontal dimension. Also, these configurations do not satisfy the increasing capacity needs. To overcome this deficiency, 3D massive array configurations, such as cylindrical and spherical array configurations are recommended [6, 7]. The cylindrical array configuration, provides high directivity, and narrow beams pointing at any space direction. However, these cylindrical configurations are considered to be limited to direct visibility, and cannot be used for high buildings. A solution for this, is to use spherical array configuration, where this type of antenna array significantly enhances the data rate, link reliability and provide full 3D scanning [8].

One of the main challenges in effectively implementing large-scale arrays for mMIMO systems in 5G, is how to reduce the mutual coupling effect among the antenna elements of an array. Strong coupling effects will result in high correlation and low isolation between the antenna elements, which significantly limit the system performance, in terms of SE and EE [9].Also, mutual coupling effect can distort the power amplifier linearity, which causes interference to adjacent-channels, which is known as out-of-band (OOB) emission issue [10]. Since, mMIMO systems require that a large number of antenna elements of a large-scale array have to be placed in a device with limited space, reducing the mutual coupling effect by increasing the spacing distance between antenna elements, is not possible [11]. Therefore, traditional techniques for mutual coupling suppression are not suitable in such crowded capacity of antenna elements.

2.2 | Antenna allocation for BSs, and hardware complexity

Adequate adjusting of BS's antennas is an important issue that mMIMO systems need to overcome, in order for this technology to be implemented in 5G. Since the number of antenna elements in mMIMO is significantly large, existing traditional allocation schemes fail to apply on these systems. There are many reasons for this; firstly, in mMIMO for each additional antenna the data-rate gain is not constant, which means that adding two antennas does not guarantee that the transmission rate is doubled. Secondly, in mMIMO the performance of the link depends on both sides' antennas rather than just a single BS, which makes the resource constraints more complicated, and a challenging problem to solve [12]. This opens the research field to come up with brand new antenna scheme assignment that solve the antenna allocation problem in mMIMO.

As the number of antenna increases in mMIMO systems, the processing cost and hardware complexity at the BS increase as well. The reason is that the number of radio frequency chains

(RFC), is associated with the number of antennas in the system [13]. To solve this problem, antenna selection methods are proposed in the literature, which can be used to implement fewer RFC than the number of available antennas, by carefully selecting a number of transmitting/receiving antenna from the large-antenna array [14]. With the use of this technique, the operating cost can be significantly reduced for mMIMO systems; however, it is impracticable to obtain the optimum antenna selection, due to high computational complexity [15]. Therefore, more research on new antenna selection techniques is needed for mMIMO in order for them to be implementable in 5G systems.

2.3 | Pilot contamination in time division duplex (TDD) systems

TDD systems make use of the same frequency block for uplink and downlink, while the separation happens in time. The channel state information (CSI) is acquired for the uplink when the users send their mutually orthogonal pilot to the BS. Following this the BS correlate the received pilot with the already known pilot to estimate the channel. Due to the channel reciprocity in TDD systems, the same uplink estimated channel is used for the downlink channel estimation by the BS. In a multicellular system, where the available frequency spectrum is limited, the cells in such systems have to reuse the exact same time-frequency blocks. This makes it impossible to allocate orthogonal sequences of pilots for each user in all cells, which means all of the mutually orthogonal pilots have to be reused by those users. When a user in a neighbouring cell sends its same orthogonal pilot sequences, the channel estimation is contaminated by those pilots, this is known as the effect of pilot contamination [16]. This challenge in TDD systems of mMIMO is considered to be a major limitation toward its use in 5G. Considerable research had been done in this area to decrease the effect of pilot contamination; however, more is needed before mMIMO can be fully implanted in 5G systems.

2.4 | CSI pilot overhead in frequency division duplex (FDD)

The use of FDD systems in mMIMO is a promising approach toward the implementation of 5G, as they increase the system capacity and robustness of the link [3]. In FDD mMIMO systems, the same time block is used by the uplink and downlink, where they are separated only in frequency domain. In this case, the reciprocity of the channel as in TDD systems cannot be exploited, since there is a difference in frequency carrier between the uplink and downlink [17]. Thus, the CSI for the downlink is estimated by each user and fed-back to the BS. Having a massive number of antennas at the BS, means that users have to estimate a large number of channels associated with each antenna, which results in an enormous feedback pilot overhead [18]. Therefore, methods of reducing the high pilot overhead in FDD mMIMO systems are needed to achieve the promising high data rate for 5G.

3 | RESEARCH QUESTIONS

After choosing the topic that the systematic mapping study is going to be mapped to, the first step to start such a study is to identify the research questions. Our research investigation is designed mainly on five research questions:

- RQ1. How are the publications on mMIMO systems in 5G, distributed over the last years?
- RQ2. What are the challenges regarding antenna design and channel estimation that mMIMO systems face, toward its implementation in 5G?
- RQ3. What are the existing solution approaches concerning those challenges?
- RQ4. Regarding the state-of-the art solutions to the mentioned open research issues, which are the most cited?
- RQ5. What are the future research agenda?

To answer the mentioned research questions, we decided to conduct a systematic mapping study on the area of antenna design and channel estimation challenges in mMIMO. In the literature, there exist some work that review the concept of mMIMO and its implementation in 5G in general; however, there is no secondary study that is up to date and reviews all the challenges that are associated with antenna design combined with review of all open research issues related to channel estimation. More specifically, in [16], the authors gave an overview of mMIMO advances based on published literature before 2017. In [2], the survey was done on the evolution of mmWave mMIMO systems before the year 2018, and its possible implementation in 5G. The author in [19] reviewed a specific type of mMIMO, which is based on printed multi-antenna systems. Review on mMIMO hardware impairments and challenges was done in both [20] and [21]. In [22], the authors reviewed the issue of limited feed-back in mMIMO. The secondary studies mentioned do not concentrate on the research efforts on antenna design and channel estimation challenges. Therefore, there is an essential need for a systematic mapping study to identify and classify research challenges in the mentioned areas of mMIMO implementation in 5G, compare the existing state-of-the art solutions, and to give future research directions.

4 | RESEARCH METHODOLOGY

In this section, we describe the research instruments used for conducting the review, and the characterization framework used to classify the chosen primary studies is presented. To choose the relevant papers related to our research questions, the following inclusion criteria (IC), and exclusion criteria (EC) were performed:
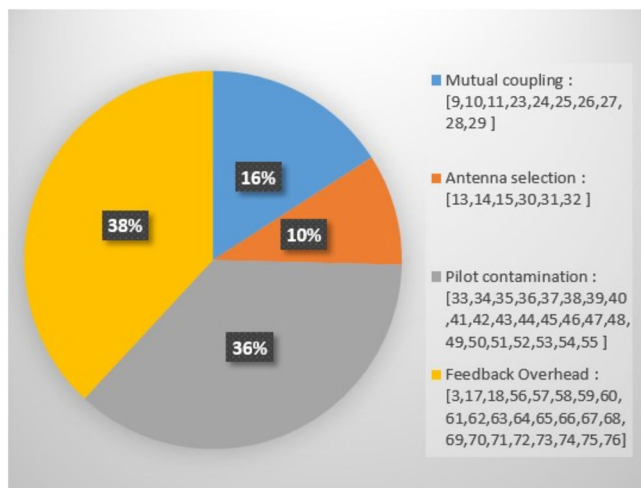
FIGURE 1 Study distribution of mMIMO antenna design and channel estimation challenges
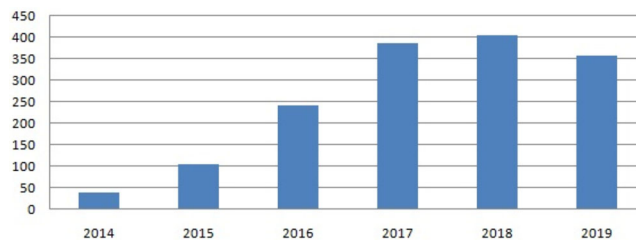

FIGURE 2 Papers published per year regarding massive MIMO

FIGURE 3 Papers published per year regarding challenges and open research issues on massive MIMO implementation in 5G

IC1: Papers that contain state-of-the art solutions and/or general studies on mMIMO systems, regarding antenna design challenges, and channel estimation issues.

EC1: Papers that present other open research issues toward mMIMO implementations in 5G that are not in the scope of our study.

EC2: Articles that are summary of conference, poster summary, keynote talks, editorial and Ph. D. thesis.

After these IC and EC were applied, the final reference list contained 63 primary studies that are relevant and directly related to the research questions asked in the previous section.

In this research we analysed the mMIMO domain with a focus on antenna design challenges and channel estimation issues, and then identified specific parameters with respect to research questions, RQ2 and RQ3. In order to systematize those parameters, we categorize them into two main clusters, built on the two main related challenges that answer the research questions mentioned early. The subheadings were identified according to the scan of the selected primary studies after the filtering round.

The key terms which were extracted from the selected studies, helped to categorize them in terms of specific challenges and open research issues, regarding antenna design and channel estimation. Figure 1 gives the terms extracted that give an understanding of key research concerns regarding those challenges in mMIMO implementation for 5G systems.

The main clusters and their subheadings that construct our comparison framework are as follows:

- Massive antenna array design challenges:
  - Mutual coupling effect and choosing of the separation distance between the antenna elements in massive antenna arrays.
  - The need for new antenna selection schemes to support mMIMO implementation in 5G systems to reduce hardware complexity.
- Perfect channel estimation challenges:
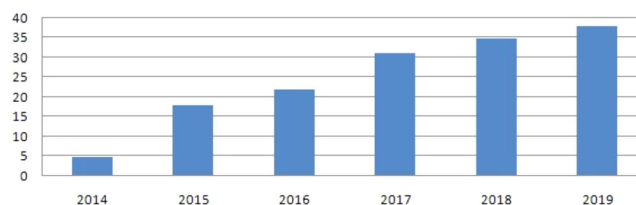
  - Pilot contamination in TDD mMIMO systems.
  - CSI feedback overhead in FDD mMIMO systems.

5 | ANALYSIS OF THE LITERATURE SURVEY

The key terms extracted from the studies, which are based on the asked research questions mentioned previously, are addressed. The distribution of publications on mMIMO systems in general, and the implementation challenges for those systems in 5G over the years of 2014 till 2019, are shown in Figures 2 and 3, respectively. It is seen that with only a few published studies in 2014 regarding the concept of mMIMO in general and the challenges of implementing mMIMO systems in 5G in specific, there has been a dramatic increase in the following years, which shows a significant interest in this research field.

In this section, we report the latest progress of research on challenges in mMIMO systems, in the context of mutual coupling, antenna selection, pilot contamination and feedback overhead, by focusing on the recent published literature between the year 2017 and the second quarter of the year 2020.

Tables 1 and 2 represent mMIMO antenna design challenges and the proposed solution extracted from the selected studies between 2017 and second quarter of 2020. The main two challenges are mutual coupling effect and antenna selection of massive antenna arrays.

In [23], a non-uniform antenna array design is proposed, where the intra-array elements are packed close to each other to fit in the limited space of the BS, while the sub-arrays are

TABLE 1 State-of-the-art proposed solutions for mutual coupling

Ref.	Design challenge	Proposed solution	Number of antenna elements	Operating frequency	Results approach
[11], 2017	Mutual coupling of massive antenna array elements	Array-antenna decoupling surface	8-element array antenna	2.45 GHz	Experimental along with simulation results
[23], 2017	Mutual coupling of massive antenna array elements	Non-uniform linear antenna array design	Dividing the antenna-array to sub-arrays with uniform spacing	2 GHz	Simulation results
[24], 2018	Mutual coupling of massive antenna array elements	Use of metal mender line strips	16-element array antenna	3.2–5 GHz	Simulation results
[25], 2018	Mutual coupling of massive antenna array elements	Three-port polarization and pattern diversity antenna design	6-element array antenna	2.574−2.647 GHz	Experimental along with simulation results
[9], 2019	Mutual coupling of massive antenna array elements	Graphene-based frequency selective surface (FSS)	4-element array antenna	1.1–1.7 THz	Simulation results
[10], 2019	Mutual coupling of massive antenna array elements	Decoupling ground technique	16-element array antenna	4.8–5 GHz	Simulation results
[26], 2019	Mutual coupling of massive antenna array elements	A transmission-line-based decoupling technique	16-element array antenna	2.45 GHz	Experimental along with simulation results
[27], 2019	Mutual coupling of massive antenna array elements	Molecule fractal structure antenna design	4-element array antenna	2.4–10.6 GHz	Experimental along with simulation results
[28], 2019	Mutual coupling of massive antenna array elements	Frequency-selective surface design approach	4-element array antenna	0.69–0.96 GHz and 3.5–4.9 GHz	Experimental along with simulation results

well separated. Due to the reduction of correlation between the sub-arrays signals, the inter-user interference cancellation is increased, and the systems performance is enhanced. To reduce mutual coupling effect between array-antenna elements, an array-antenna decoupling surface (ADS) is proposed in [11]. An ADS consists of a thin surface placed in front of the array antenna, the surface is composed of small metal patches, which can be easily implemented for large-scale antenna arrays. Decoupling is achieved in [24] by embedding metal meander line strips horizontally and vertically between the antenna elements. By the use of those metal line strips, an additional coupling path is provided to reduce the coupling effect between the ports. A three-port antenna design, exhibiting pattern diversity is proposed in [25]. In the proposed method, the radiating elements comprises of a ring which is loaded with periodical interdigital capacitors. The selective excitation properties of the three ports of the proposed antenna enables dual-polarized and omnidirectional broadside radiation patterns. Using this method, the mutual coupling between any pairs of ports in the three-port proposed antenna system is found to be less than −20 dB. The mentioned design showed to have low mutual coupling effect and uncorrelated radiation patterns, which makes it a good candidate for implementation in mMIMO systems for 5G applications. A decoupling technique using transmission-line-based
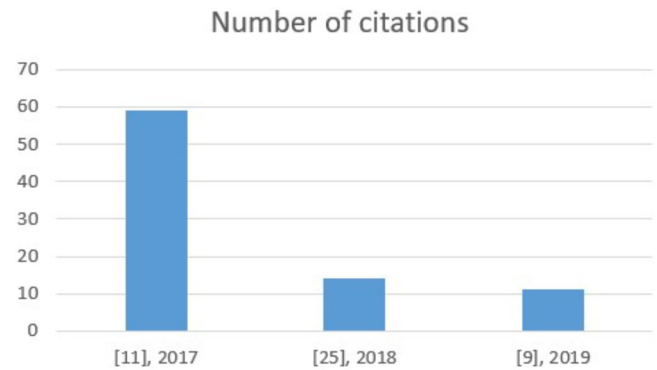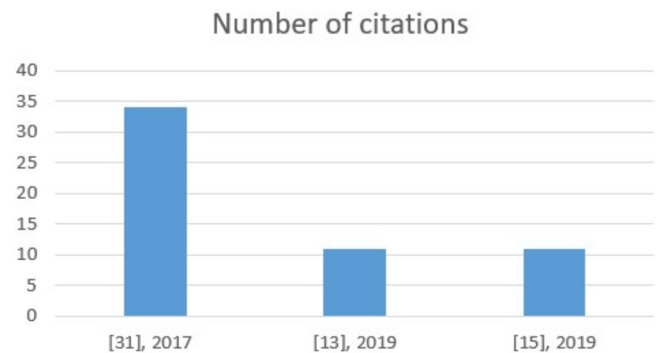
decoupling network is presented in [26]. The decoupling network is realized in a single layer, with compact size and low insertion loss, which can be used for phased array mMIMO systems. To enhance the isolation of antenna array elements in mMIMO, a decupling ground concept is introduced in [10]. By adjusting the ground plane shape under each antenna element, the isolation is improved by making the mutual coupling from the ground plane and the free space out of phase. An isolation improvement using molecule fractal structure is given in [27]. The isolation is achieved by orthogonal orientation of the antenna perpendicular elements. This method shows an impedance bandwidth ($S_{11} < −10$ dB) in the range between 2.4 and 10.6 GHz, achieving an isolation of better than −20 dB over the entire UWB range. The proposed approach was compared with 11 different approaches which were reported in literature ([27], Table 2). It is found that the proposed method is compact in terms of size and provides high isolation without a decoupling structure. In [28], frequency selective surface (FSS) is used as a decoupling technique. An FSS is introduced between the two layers of the antenna, where the high frequency antenna elements are placed above the FSS layer, and the lower operating frequency antennas are placed under the FSS. The different band antennas mutual coupling was effectively suppressed by the use of FSS technique. Also, in [9], reducing the mutual

TABLE 2 State-of-the-art proposed solutions for antenna selection

Ref.	Design challenge	Proposed solution	Number of antennas at transmitter and receiver (Tx × Rx)
[30], 2017	Antenna selection	Capacity-based reduced-complexity exhaustive search(CRCES) and norm-based reduced-complexity exhaustive search (NRCES) technique	64 × 10
[31], 2017	Antenna selection	Joint antenna and user (AU) algorithm	Several scenarios including 16 × 10 to 16 × 24 32 × 10 to 32 × 24
[14], 2018	Antenna selection	Group layer MU-MIMO scheme	32 × 32
[32], 2018	Antenna selection	Channel norm statistics based selection method	64 × 64
[13], 2019	Antenna selection	Use of user clustering techniques	Several scenarios including 40 × 160 60 × 160
[15], 2019	Antenna selection	Use of algorithm based on calculation of the highest achievable rate of an individual antenna element in an antenna array	125 × 3

FIGURE 4 The three most cited solution approach of mutual coupling for mMIMO

FIGURE 5 The three most cited solution approach for antenna selection in mMIMO

coupling effect in dense antenna-arrays for multi-band mMIMO systems, was achievable by using graphene-based FSS. In this proposed technique, by placing the FSS structure in between the array elements, the mutual coupling effects were reduced. The isolation is improved further by inserting the FSS decoupling structure into the substrate as well. By doing so, the electromagnetic wave propagation is blocked in the substrate. The reported results show that both the coupled electric and magnetic fields were eliminated, using the FSS decoupling structure. A coprime cubic array (CCA) design configuration is proposed in [29]. The CCA consists of two uniform cubic subarrays, which can extend the antenna element spacing in a given array, by selection of three pairs of coprime integers. The proposed CCA configuration, can effectively decrease the mutual coupling effect, and increase the array aperture compared to traditional uniform cubic array (UCA) design configurations.

A transmit-antenna selection scheme for mMIMO systems is proposed in [30]. The scheme consists of two methods, which are capacity-based reduced-complexity exhaustive search (CRCES) and norm based reduced-complexity exhaustive search (NRCES). In the proposed method, the criteria of selection of candidate transmit-antenna subset, is based on SNR maximization. It is found that the CRCES method is well suited for low SNR values, and has the capability to improve the system performance in terms of capacity. In [31], antenna selection is performed by using an algorithm which selects can-

didate antennas according to user scheduling techniques, and search for the highest achievable channel gain. The favourite antennas are sought from limited candidate antennas which are favourable to the related users. Then by using the proposed joint antenna and user (AU) contribution algorithm, selection of antennas and scheduling of users, is performed for multi-band multi-user scenario. In [32], an mMIMO transceiver system design for 5G applications is proposed. The antenna selection process in the mentioned design, was based on channel norm statistics. A group layer multi-user MIMO scheme with antenna selection algorithm is proposed by [14]. The best subset of antennas are selected according to their channel condition. The proposed scheme achieved significant reduction in RF chain, which can be used for 5G mMIMO systems. In [15], the antenna selection algorithm is based on calculating the achievable rate. The antennas with the highest transmission rates are chosen at the BS. The proposed technique provided good quality of service for the whole uplink of the mMIMO network. An antenna selection algorithm based on user clustering is proposed in [13]. The clusters are based on the channel conditions and the number of accessible RF chains. The antenna selection algorithm then follows minimum rate and power constraints to effectively select the candidate antennas.

Figures 4 and 5 show the most cited solutions for mutual coupling and antenna selection issues, based on google scholar number of citations till the second quarter of 2020.

Tables 3 and 4, represent mMIMO channel estimation challenges and the proposed solution extracted from the selected studies between 2017 and second quarter of 2020. The main two challenges are pilot contamination in TDD mMIMO systems and feedback overhead in FDD mMIMO systems.

In [33], the authors introduced superimposed pilots scheme for uplink channel estimation as a solution to pilot contamination in mMIMO. By using this scheme, it is found that the channel estimation is improved due to the reduction of interference, since the pilots are transmitted alongside with the transmitting data. A channel estimator for multi-cell mMIMO TDD system is presented in [34]. The proposed scheme for the uplink training process is based on the use of Zadoff-Chu (ZC) pilot sequence. It was found that the proposed estimator performs as well as the minimum mean square error (MSE) estimator and is able to perform under strong pilot contamination without prior knowledge of noise power and inter-cell large scale fading coefficients. Authors in [35], proposed an estimation algorithm for Rician fading channels based on statistical channel information and contaminated CSI. The line-of-sight (LOS) component of the BS users are estimated based on the angle of arrival (AoA) and the contaminated CSI, then using those LOS components the data are detected, which are used to update the CSI estimate through an iterative process. Simulation results show that in coherence-time-limited systems high SE is achieved, which makes the proposed scheme a good channel estimator candidate for mMIMO systems using Rician fading channels. In [36], a channel estimation scheme is based on assigning specific orthogonal variable spreading factor (OVSF) code row for each BS, and ZC sequences are then used for uplink pilot training. Element-wise multiplication of the ZC sequence at each BS with its OSVF code row is then performed to generate orthogonal pilot sequences among the neighbouring cells. The proposed scheme is able to eradicate pilot contamination, resulting in interference-free downlink transmission and enhanced sum-rate performance. For broadband mMIMO systems using OFDM modulation, a joint angle-delay subspace channel estimator is used in [37]. Based on the parametric channel model, the concept of joint angle-delay subspace is used, along with low-complexity and low-rank adaptive filtering algorithm. Due to the reason that channel statistics are typically unknown, a robust MMSE estimator is developed. This estimator takes into consideration the worst precondition of pilot decontamination, bearing in mind that fully overlap occurs in the joint angle-delay subspaces of the interfering users. A semi-blind channel estimation algorithm is given in [38]. The proposed estimation algorithm requires neither pilot scheduling nor co-operation among the cells. The proposed signal is first projected onto the subspace with minimal interference, and an initial channel estimation is made based on the small number of pilot symbols. After that, the data symbols are detected and the channel estimation is distinguished alternatively. The proposed algorithm has low complexity and is able to effectively reduce the pilot contamination effect. An eigenvalue-decomposition based channel estimator is presented in [39] as a solution to pilot contamination. Even though that the eigenvalue-decomposition based channel

estimator is an efficient solution to overcome pilot contamination, this method performance is dependent on the number of BS antennas and the accuracy of the sample covariance matrix. It is found that the rate loss is proportion to the BS antenna, and when those antennas are finite, there is always a non-zero rate loss in an mMIMO system using the eigenvalue-decomposition based estimator. Also in [40], time-shifted pilot scheme is used to combat pilot contamination. The channel estimator presented is divided to two stages. The interface from other cells is reduced by introducing null symbol periods determined using the beamforming vectors after that the channel estimation is performed. Simulation results show that the proposed scheme can effectively reduce the pilot interference and improve SE in high SNR region.

In [41], a channel estimation method for OFDM mMIMO systems is proposed using least squares channel estimation (LSCE). Simulation results show that the channel estimation is enhanced by overcoming pilot contamination, and the performance of the system is improved in terms of Bit Error Rate (BER). In [42], graph colouring-based pilot assignment (VGC-PA) algorithm in combination with the existing post-processing discrete Fourier transform (DFT) filtering is proposed for channel estimation to enhance the system capacity and mitigate inter-cell interference between users sharing the same pilots. A channel estimation algorithm based on joint singular value decomposition (SVD) and iterative least square with projection (SVD-ILSP) is proposed in [43]. The proposed algorithm overcomes the disadvantage of finite sample data assumption of the covariance matrix that exist in the SVD-based semi-blind channel estimation structure. The optimization method is to combine both the SVD and the ILSP algorithms, through applying the principle of iteration. Simulation results show that the proposed algorithm can mitigate pilot contamination impact and accurately obtain CSI with low computational complexity. Authors in [44], proposed a channel estimation scheme using factor analysis which decomposes the space supported by the received signal convenience matrix into three subspaces. Simulation results show that by exploiting the spatial correlation using factor analysis, the proposed channel estimation scheme can mitigate the impact of both pilot contamination and noise interference. A block-diagonal Grassmannian line packing (BDGLP) approach to mitigate pilot contamination is given in [45]. Specific sequences for cells are designed using GLP, and then extended to form the superimposed pilot matrices for the users. Then a channel estimation method based on Tikhonov regularization (TR) is used. Numerical results show that the proposed technique improves the accuracy of channel estimation and further improve the SE. In [46], the authors propose a semi-blind uplink interference suppression scheme for multi-cell mMIMO. The proposed method employs a blind interference suppression scheme which is a constant modulus algorithm (CMA) and uses MMSE post coding weight as a primary weight of the CMA. Although MMSE weight cannot suppress interference due to pilot contamination, it can be beneficial to the CMA to capture the desired signals that is needed for the CMA to effectively operate. In the next step, a decision feedback channel estimation (DFCE) is then presented to further enhance the CSI

TABLE 3   State-of-the-art proposed solutions for pilot contamination

Ref.	Channel estimation issue	Channel type	Proposed channel estimation strategy	Performance metric
[33], 2017	Pilot contamination	Additive White Gaussian Noise (AWGN)	Non-iterative scheme based on superimposed pilots	BER, sum rate and approximate rate per user
[34], 2017	Pilot contamination	Multipath channel	ZC sequences and minimum-variance unbiased estimator (MVUE) method	MSE
[35], 2017	Pilot contamination	Rician fading channels	LOS angles of arrivals (AOAs)	BER and SE
[36], 2017	Pilot contamination	Fast fading	Orthogonal variable spreading factor (OVSF) code row and a set of Zadoff–Chu (ZC) sequences	Sum rate
[37], 2017	Pilot contamination	Multipath channel	Joint angle-delay subspace	NMSE
[38], 2017	Pilot contamination	AWGN	Semi-blind channel estimation algorithm	NMSE and BER
[39], 2017	Pilot contamination	Fast-fading channel	Eigenvalue decomposition	Achievable rate and the symbol error rate
[40], 2017	Pilot contamination	Rayleigh fading	Time-shifted pilot scheme	NMSE and SE
[41], 2020	Pilot contamination	Rayleigh fading	Least squares channel estimation (LSCE)	Bit error rate(BER)
[42], 2018	Pilot contamination	Multi-path channel	Vertex graph colouring-based pilot assignment (VGC-PA) algorithm	Average MSE
[43], 2018	Pilot contamination	Small-scale and large-scale fading	Joint singular value decomposition (SVD) and iterative least square with projection (SVD-ILSP)	MSE and SE
[44], 2018	Pilot contamination	AWGN	Factor analysis technique	Estimation error variance
[45], 2018	Pilot contamination	AWGN	Block-diagonal Grassmannian line packing (BDGLP) approach	NMSE and SE
[46], 2018	Pilot contamination	AWGN	Blind interference suppression scheme	BER and SINR
[47], 2019	Pilot contamination	Small-scale and large-scale fading	Hybrid pilot-aided channel estimation technique based on time-multiplexed (TM) pilot and time-superimposed (TS) pilot	Achievable data rate
[48], 2019	Pilot contamination	AWGN	Coordinated pilot sequence DESIGN	MSE
[49], 2019	Pilot contamination	Block-fading	Pilot assignment strategy and pilot design-based channel estimation with Zadoff-Chu (ZC) sequences	NMSE
[50], 2019	Pilot contamination	AWGN	Channel estimation scheme based on spatial spectrum analysis	MSE
[51], 2019	Pilot contamination	Multipath channel	CS based algorithm with non-zero neighbourhood (NZN) structure scheme	Average pilot length and sum rate
[52], 2020	Pilot contamination	AWGN	Least-squares (LS) estimation using deep neural network (DNN)	Normalized mean square error(NMSE)
[53], 2020	Pilot contamination	Rayleigh fading	Orthogonal pilotreuse sequence	Average data rate
[54], 2020	Pilot contamination	Block-fading	Use of superimposed (SP) pilots in combination with time-multiplexed (TM) pilots	Mean square error (MSE) and SE
[55], 2020	Pilot contamination	Small-scale and large-scale fading	Space-alternating generalized expectation-maximization (SAGE) based semi-blind estimator	BER,MSE and SE

TABLE 4 State-of-the-art proposed solutions for feedback overhead

Ref.	Channel estimation issue	Channel type	Proposed channel estimation strategy	Performance metric
[56], 2017	CSI feedback overhead	AWGN	Robust closed-loop pilot and CSIT feedback resource adaptation framework	MSE
[57], 2017	CSI feedback overhead	Rayleigh fading	Low-rank covariance-assisted downlink training	NMSE
[58], 2017	CSI feedback overhead	WINNERII	Exploiting the angle domain channel sparsity	MSE
[59], 2017	CSI feedback overhead	Time-varying block Rician fading channel	Estimation of the strongest AoAs at both the BSand the users	Average achievable rate per user
[60], 2017	CSI feedback overhead	Block-fading	Threshold-based estimation	MSE
[61], 2017	CSI feedback overhead	Spatio correlation channel	Beam-blocked sparsity	Achievable sum rate and NMSE
[62], 2017	CSI feedback overhead	AWGN	Spatial downlink channel estimation scheme	Sum rate and BER
[63], 2018	CSI feedback overhead	AWGN	Single-bit sparse maximum-likelihood estimation (MLE) and single-bit compressed sensing	NMSE, beamforming gain and sum capacity
[64], 2018	CSI feedback overhead	AWGN	Beamformed channel state information reference signalCSI-RS transmission mechanism	SE
[65], 2018	CSI feedback overhead	AWGN	Estimation algorithm based on projection methods in an infinite-dimensional Hilbert space	MSE
[66], 2018	CSI feedback overhead	Quasi-static channel	Sparse adaptivematching pursuit (SAMP) algorithm	NMSE
[67], 2018	CSI feedback overhead	One-ring scattering model	Interference alignment and soft-space-reuse (IA-SSR)	Sum rate and MSE
[68], 2018	CSI feedback overhead	Frequency selective channel	Block Bayesian matching pursuit (BBMP)	NMSE
[69], 2018	CSI feedback overhead	Time-varying channel	Combination of CS, block Iterative-support-detection (block-ISD), angle-of-departure (AoD) and structured compressive sampling matching pursuit (S-CoSaMP) algorithms	NMSE
[3], 2019	CSI feedback overhead	AWGN	Deep learning with superimposed coding (SC)	BER and NMSE
[17], 2019	CSI feedback overhead	One-ring channel model, AWGN	Joint pre-coding and scheduling algorithm	Cell average throughput
[18], 2019	CSI feedback overhead	FDD, fasttime-varying	Structured compressive sensing (SCS)	Normalized mean squared error
[70], 2019	CSI feedback overhead	Multipath channel	Angular scattering function (ASF) with sparsifying precoder	Sum rate
[71], 2019	CSI feedback overhead	Multipath channel	Newtonized orthogonal matching pursuit (eNOMP) algorithm	NMSE and sum rate
[72], 2019	CSI feedback overhead	AWGN	CS scheme	NMSE and BER
[73], 2019	CSI feedback overhead	Small-scale and large-scale fading	DNN approach for non-linear CSI structure	Sum rate
[74], 2019	CSI feedback overhead	Channel model is formulated by the authors using third order tensor	Pilot-data superposition	Sum rate
[75], 2020	CSI feedback overhead	Rayleigh fading	Angle reciprocity of multipath components estimation technique	MSE and SE
[76], 2020	CSI feedback overhead	Quasi-static frequency selective fadingchannel	Quantized partially joint orthogonal matching pursuit (Q-PJOMP) and quantized partially joint iterative hard thresholding (Q-PJIHT) compressed sensing (CS) algorithms	NMSE and BER

estimation. Simulation results reveal that the proposed scheme can reduce pilot contamination and improve outage probability.

A hybrid pilot-aided technique for channel estimation of multi-cell multi-user mMIMO systems is proposed in [47]. The hybrid pilot-aided estimation technique consists of both time-superimposed (TS) pilot and time-multiplexed (TM) pilot, and thus allow a better solution to pilot contamination compared with conventional pilot schemes. Theoretical and numerical simulation results show that by using the proposed scheme a higher UL rate can be achieved. A matrix fractional programming (FP) approach used in coordinating the uplink pilots across multiple cells is proposed in [48] to overcome pilot contamination. The proposed algorithm guarantees reduction of the weighted sum MSE of channel estimation and numerical results show that it can outperform conventional pilot reuse methods, especially for the cell-edge users. In [49], a pilot design-based channel estimation scheme is proposed by employing perfect auto-correlation property of Chu sequences, aiming to obtain accurate CSI by overcoming pilot contamination. Simulation results show that the proposed pilot assigning strategy has low computational complexity and can be applied to mMIMO systems. A channel estimation method for 2D mMIMO systems with uniform rectangular array (URA) antenna is proposed in [50]. The spatial spectrum is derived using the AoA and the spatial frequency. Then using spectrum analysis, the channel gains can be estimated. Also, zero padding and interpolation methods are used to improve the computational resolution of the proposed method. Simulation results show that the accuracy of channel estimation is improved by using this scheme in mMIMO systems. A compressed sensing (CS) based channel estimation algorithm is proposed in [51]. To eliminate pilot contamination, a non-zero neighbourhood (NZN) pilot assignment scheme is used. Based on this scheme the interference region of each user is defined. Simulations show that the proposed scheme achieves good performance in terms of average pilot length and sum rate.

A combination of deep neural network channel estimator followed by conventional LS estimation technique is given in [52]. The proposed scheme is found to be more suitable in dealing with pilot contamination and co-channel interference compared to traditional methods based on LS alone without the use of deep learning. A channel estimation scheme applying orthogonal pilot reuse sequence for edge users is proposed in [53]. This is performed based on large-scale fading. The scheme is evaluated by using zero-forcing precoding maximum ratio transmission techniques. Interfering users in neighbouring cells are recognized based on an assessment of large-scale fading. These interfering users are then included in the joint channel processing. By assigning orthogonal pilot reuse sequences to the centre user and the edge users based on their levels of pilot contamination, the channel quality of users is enhanced. Simulation results indicate that the channel approximation and the systems performance in the downlink are improved as well as enhancing the achievable data rate. In [54], superimposed (SP) pilots combined with TM pilots are used to estimate the CSI. The TM pilots reduces the interference, which was a critical problem in using SP pilots based channel estimators. Numerical results show that
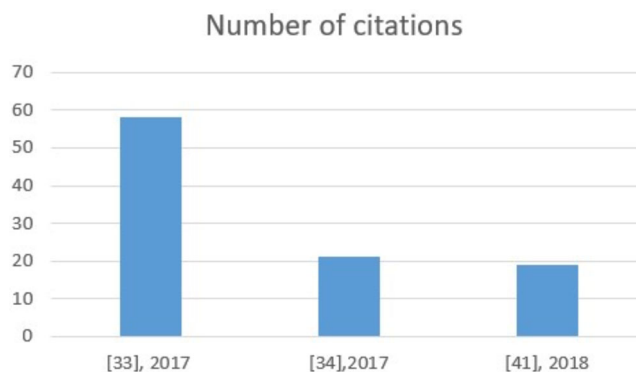

FIGURE 6 The three most cited solution approach for pilot contamination challenge in mMIMO

the interference is reduced using the proposed method, and thus the SE of mMIMO is improved. A space-alternating generalized expectation-maximization (SAGE) based semi-blind channel estimator is proposed in [55]. The proposed channel estimation method is divided into two stages. First, a linear minimum mean squared error (LMMSE) pilot-aided estimator is initially used for channel estimation. Secondly, the initial estimation is then iteratively updated using the SAGE algorithm. Simulation results show that the proposed algorithm has improved the CSI accuracy and enhanced the SE of mMIMO systems.

Figure 6 shows the most cited solutions for pilot contamination issues in TDD mMIMO, based on google scholar number of citations till the second quarter of 2020.

In [56], a multi-user mMIMO system with closed-loop pilot and CSI feedback resource adaptation framework is proposed. The framework includes pilot resource adaptation, joint compressive CSI recovery and CSI quality estimation. From simulation results, the framework proposed enhanced CSI estimation performance, and improved robustness against dynamic channel sparsity. To reduce downlink training overhead exploiting of low-rank structure of the channel covariance matrix is done in [57]. The behaviour of the MMSE estimator is studied when the covariance matrix has a low-rank structure. Then to estimate the covariance matrix, a training free scheme is proposed. Results show that the estimated covariance matrix used for MMSE estimator achieves better performance compared with the CS method, and is robust to angular spread estimation error and against AoA distribution mismatch. An angular domain pilot design and channel estimation scheme is given in [58]. An index calibration algorithm is used to estimate the DL dominant angular set from UL channel. For pilot design partial orthogonal pilot and complete orthogonal pilot designs are proposed. Simulations demonstrate that the given scheme can achieve larger DL throughput and reduce feedback overhead providing good MSE performance. A channel estimation algorithm that does not require CSI feedback from the users is proposed in [59]. The proposed algorithm aims to estimate the strongest AoAs at both the UE and BS. Then users send orthogonal pilot symbols based on the estimated strongest AoAs. Analytical and simulation results prove that the proposed scheme can be

applicable for both sparse and non-sparse mmWave channel environments. A threshold-based method for channel estimation is proposed in [60]. The optimal threshold is obtained as a function of sparsity, channel variance, and noise variance. The simplified threshold is a function of noise variance only. The proposed technique has good estimation accuracy, with reduced feedback overhead. In [61], a beam-blocked compressive scheme for channel estimation is proposed. Pilot overhead is reduced by taking benefit of inherent block sparsity structure of channel matrix in beam-space. Then, by using an optimal block orthogonal matching pursuit algorithm the CSI can be accurately estimated at the BS using the limited number of pilots. Depending on statistical spatial correlation channel clusters of the UL and DL, a channel estimation scheme is proposed in [62] for FDD mMIMO systems. Given an arbitrary frequency band gap between the channels, the UL and DL channels, this method construct a transformation matrix that precode the UL channel based on the dominant estimated angles of departure. The proposed scheme is found to be able to accurately estimate the CSI at the BS without the cost of user feedback overhead, as well as without prior knowledge of the channel statistics.

Authors in [63] proposed limited feedback algorithms to solve feedback overhead in 5G mMIMO systems. The feedback framework uses dictionary-based sparse channel estimation algorithms that have low computational complexity. The used dictionaries are related with both the angle of departure and the angle of arrival that precisely comprise the antenna directivity patterns at both ends of the link. Simulations reveal that the proposed algorithms is able to accurately estimate the channel using small number of feedback bits. A CSI acquisition scheme for mMIMO FDD systems is proposed in [64] that uses limited feedback algorithms utilizing beam-formed CSI reference signal transmission mechanism. The algorithms proposed is divided into stages that consist of multiple wideband beamforming vectors selection and sub-band combination coefficients calculation. Simulations show that the prohibitive amount of feedback is avoided, and the SE of the system is enhanced. An estimation algorithm that exploit properties of channel reciprocity in the angular domain, using projection methods in an infinite-dimensional Hilbert space is proposed in [65]. Evaluation of the proposed scheme was done using Monte Carlo simulations, and results prove that higher accuracy of channel estimation was achieved with low computational complexity. In [66], modified sparse adaptive matching pursuit (SAMP) algorithm is introduced to reduce feedback overhead in FDD mMIMO systems. The SAMP algorithm is presented to handle the issue when the massive MIMO channel sparsity is unknown. To overcome the limitations of the SAMP algorithm such as fixed step size and too much iterations, the modified SAMP (M-SAMP) is presented. To reconstruct the signal, this approach combines the initial sparsity estimating, the signal segmenting, and the variable step size. Simulation results show that proposed algorithm achieves better performance in terms of computation time and accuracy compared to subspace tracking (SP), orthogonal matching pursuit (OMP) algorithms. In [67], a cooperative transmission scheme based on interference-alignment and soft-space-reuse (IA-SSR) with low-cost channel

estimator is proposed. The cooperative transmission structure under a two-stage precoding framework, is based on the IA-SSR scheme. Explicitly, the cell-edge users and the cell-centre ones, are treated separately to fully exploit the spatial degrees of freedoms. Later on, to maximize the capacity of the network, the optimal power allocation policy is established. The cooperative transmission structure under a two-stage precoding framework, is based on the IA-SSR scheme. Explicitly, the cell-edge users and the cell-centre ones, are treated separately to fully exploit the spatial degrees of freedoms. Later on, to maximize the capacity of the network, the optimal power allocation policy is established. A variety of numerical results, representing the sum-rate per cell-edge and cell-centre clusters, as well as the MSE performance of the proposed channel training scheme are presented to demonstrate the efficiency of the proposed algorithm. A channel estimation approach using block Bayesian matching pursuit (BBMP) is given in [68]. In this approach, the channel estimation issue is formulated as a block sparse recovery problem, in which the prior probability for block support set is derived accordingly. Based on the equivalent sensing matrix, the block index is selected based on a selection metric, by exploiting the maximum likelihood criterion. Additionally, by applying a matching pursuit method, the update criterion is derived for the selection metric once the dominant support set augments with the iteration. A combination of compressed-sensing (CS), structured compressive sampling matching pursuit (S-CoSaMP), angle-of-departure (AoD) and block iterative-support-detection (Block-ISD) algorithms are given in [69] as a solution to reduce feedback overhead of channel estimation. Simulation results show that the proposed technique reduces the pilot feedback overhead by a significant percentage which improves the overall system SE and EE.

In [70], the authors presented an estimation that exploits the reciprocity of the angular scattering function, which is used to estimate the users' DL covariance matrix from UL pilots. Simulations show that the proposed method can perform better than CS-based estimation methods as it can be used even if the available DL pilot dimension is less than the inherent dimension of the channel vectors. An estimation framework developed using enhanced Newtonized orthogonal matching pursuit (eNOMP) algorithm is given in [71]. The algorithm is used to extract from the uplink the frequency-independent parameters, which can be used to develop the downlink training scheme. Numerical results show that the proposed framework can reconstruct the CSI with small amount of feedback and training overhead. In [72] the authors proposed a CS estimation scheme that improves the coding sampling matching pursuit (CoSaMP) algorithm, for FDD mMIMO systems by proposing structured sparse adaptive (CoSaMP) algorithm. Simulation results show that the proposed algorithm has good performance in low SNR and can reduce the pilot overhead, which provides better SE. Instead of exploiting linear CSI structures, to attain dimensionality reduction, a deep neural network (DNN) approach is proposed in [73]. Case studies based on ray-tracing simulation show that the proposed approach can accurately estimate the CSI, reduce pilot feedback overhead and thus enhance the wireless system performance. In [3], the authors combined deep learning DL with superimposed

coding (SC) as a solution for CSI feedback overhead. In this approach, the downlink CSI is spread and then superimposed on the uplink user data sequences. A multi-task neural network architecture is then proposed at the BS, by unfolding two iterations of the MMSE criterion-based interference reduction, the downlink CSI and the uplink user data sequences are recovered. Additionally, a subnet-by-subnet technique is exploited to facilitate the parameter tuning and expedite the convergence rate for the network training. Simulations show that the estimation of the CSI is improved for 5G mMIMO systems without much occupation of UL bandwidth resource. Authors in [18] propose a non-orthogonal pilot design with CS based channel estimation algorithm. By taking advantage of the spatial and temporal common sparsity in delay domain of mMIMO, results show that fewer pilot overhead is achieved for accurate CSI estimation. To cope with the pilot feedback overhead issue in FDD mMIMO systems, authors in [17] proposed a design consisting of joint precoding and scheduling algorithm for multi-cell mMIMO systems. To further reduce the computational complexity of the proposed algorithm, a greedy scheduling algorithm that is compatible with proposed framework is introduced. Simulations verify that reduction of feedback overhead is achieved. The intrinsic tensor feature of the FD-MIMO channel is explored in [74], to enhance CSI estimation. The proposed estimation algorithm is based on the expectation-maximization framework via tensor as the processing data structure. Moreover, for evaluation, the Cramér-Rao lower bound is utilized as a metric. Simulation results show an increase in CSI estimations, providing flexibility in realizing trade-off points between UL and DL throughput using pilot-data superposition strategy.

In [75], multipath components angle reciprocity in the uplink and downlink is used, so that the overhead CSI in FDD mMIMO systems scales only with the served users, instead of the number of antennas. Simulation results show that the proposed estimation technique outperforms traditional gradient-descent and subspace-based techniques. A CS based algorithm is used in [76] to recover the CSI at the BS from limited and quantized feedback. By preserving one bit per dimension direction information along with the partial amplitude information, the received compressed pilots are quantized. Then, this information that is fed back to the BS, is used to recover the CSI by employing the CS algorithms proposed. Results show that the proposed algorithm overcome the problem of training and feedback overhead in FDD mMIMO system; however, this technique has a cost of high complexity.

Figure 7 shows the most cited solutions for feedback overhead issues in FDD mMIMO systems, based on google scholar number of citations till the second quarter of 2020.

6 | FUTURE DIRECTIONS

To be able to benefit from mMIMO systems in the upcoming 5G mobile network, its use with mm-wave spectrum is essential. Most of the aforementioned techniques to overcome mutual coupling issue in massive antenna array design are mainly developed based on sub-6 GHz applications and for a certain
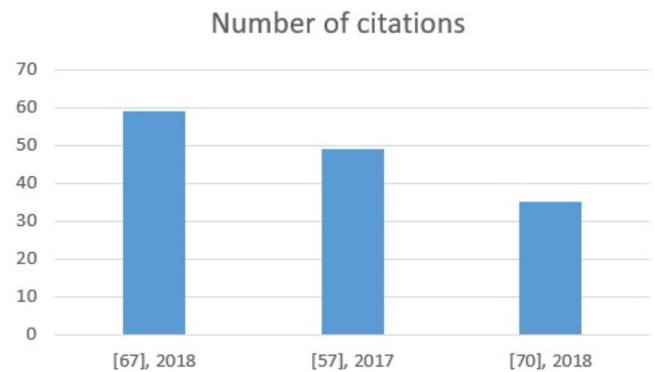

FIGURE 7 The three most cited solution approach for feedback overhead challenge in mMIMO

limited number of antenna elements used. Therefore, extra research effort is needed to investigate the possibility to use such techniques for higher frequency bands, as well as to test their validity for higher number of antennas in terms of several tens to hundreds.

For the accurate acquisition of the CSI, pilot contamination and feedback overhead need to be solved, before mMIMO can be fully integrated into future 5G wireless systems. Although good progress has recently been made in both directions, there is still a need for more research to be conducted on this area.

- Research done in [18] on SCS, needs to be extended so that the proposed scheme can be suitable for the multi-cell scenarios.
- Low computational complexity algorithms that offer optimal performance is needed for the iterative data-aided channel estimation scheme proposed in [33].
- The OVSF code row and the set ZC sequences used by [36], as a solution to pilot contamination multiplies OVSF code row at each BS with the ZC sequences. This requires that the number of multiplications is equal to the square of the number of pilot sequences. Therefore, reduction of this complexity using pilot assignment technique is needed.
- The SVD-ILSP technique proposed in [43], can be considered for FDD mMIMO scenarios, by using mmWave frequency bands.
- The BDGLP approach used in [45] is based on flat-fading channel model. The performance of this approach needs to be further improved by considering frequency selective fading model.
- Observing the performance of LS estimation technique using DNN, proposed in [52] for high mobility mm-Wave channels, will be necessary to apply this technique in future 5G systems.
- The LSCE technique proposed in [53], can be further improved by focusing on a regular pilot, where the data estimates can be preserved to enhance the channel estimates.
- The ASF used for channel estimation in [70] needs to be generalized to cover a wider category of array antenna geometries.
- For the CS channel estimation scheme given in [72], the problem of sparse structuring in the virtual angler domain need

to be explored to improve the applicability of the proposed method.

7 | CONCLUSION

Massive MIMO is considered to be one of the enabling technologies for the next generation of wireless systems (5G). With large number of antennas at the BS, simultaneously communication with multiple users using the same resources is possible. This allows higher spectral and energy efficiencies. However, this technology faces some challenges which need to be addressed before its possible implantation in 5G systems. In this paper, we provide a systematic mapping study on the state-of-the-art research efforts regarding antenna design challenges and channel estimation issues. Although there are several secondary studies in the literature that covers massive MIMO challenges in general, our paper provides a clear classification framework on the proposed solution techniques given in literature, with specific focus on the topics of mutual coupling, antenna selection, pilot contamination and feedback overhead. The paper is expected to be a road map for researchers in this field.

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