Research Perception and Analysis Towards the Channel Estimation Algorithms in MIMO-OFDM System

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***Abstract*—The core of the OFDM-based wireless communication receiver is channel estimation. MIMO is used in 4G mobile communications to augment the system's capacity by outfitting the transceiver and receiver with multiple antennas using OFDM technology. MIMO-OFDM is a popular modern wireless broadband technology, owing to its large data transmission rate, resistance against multipath fading, and excellent spectral efficiency. This technology offers consistent communication and a broad range of coverage. The precise recovery of CSI and synchronization between the sender and receiver are the two major challenges in the MIMO-OFDM system. Several estimate techniques, including 'pilot-aided, blind, and semi-blind channel estimating,' are being used to extract the channel state information. In this survey, different channel estimate methods of the MIMO-OFDM system are reviewed and analyzed. Mainly it emphasis reviewing the various channel estimation methods, their advantages and drawbacks are furnished. The performance metrics in each contribution are also presented, and the recorded best performance is manifested. Finally, research gaps are identified and discussed, paving the way for developing a novel deep learning model for channel estimation in MIMO-OFDM systems.**

Keywords—MIMO; OFDM; Channel Estimation Algorithms.

Nomenclature

Abbreviation	Description
MIMO	Multiple-Input Multiple-Output
G-SBEM	Generalized-Spatial BEM
LS-KRF	Least Squares Khatri-Rao Factorization
UE	User Equipment
MMSE	Minimal Mean Square Error
SER	Symbol Error Rate
OFDM	Orthogonal Frequency Division Multiplexing
AMA	Adaptive Multi-Frame Averaging
T-OMP	Tensor-Orthogonal Matching-Pursuit
DL	Deep Learning
NAMP	Novel Adaptive Matching Pursuit
BEM	Basis Expansion Model
LS	Least Square
QBSO	Quasi-Block Simultaneous Orthogonal Matching Pursuit
CIR	Channel Impulse Response
G-SBEM	Generalized-Spatial BEM
ADD	Angle-Delay Domain
LGM	Linear Gauss-Markov
AFD	Angle-Frequency Domain
IMOT	Improved MSE Optimum Threshold
NCT	Nonzero Channel Tap
FER	Frame Error Rate
STTC	Space-Time Trellis Coded
MLSD	Maximum Likelihood Sequence Detection
AMP	Approximate Message Passing
SBL	Sparse Bayesian Learning
CVBI	Collapsed Variational Bayesian Inference
CP	Canonical Polyadic
MSBL	Multiple Response Extension Of SBL
CS	Compressed Sensing
MLSD	Maximum Likelihood Symbol Detection
BS	Base Station
StFBP	Stage-Wise Forward Backward Pursuit
FDD	Frequency Division Duplex
OSTBC	Orthogonal Space-Time Block Coded
SBL	Sparse Bayesian Learning
MSE	Mean Square Error
EM	Expectation Maximisation
SVD	Singular Value Decomposition
OSBS	Optimized Semi-Blind Sparse
PSA	Pulse Shaping Algorithm
BCRBs	Bayesian Cramér-Rao Bounds
ML	Maximum Likelihood
BEP	Bit Error Probability
ESBL	Extended Sparse Bayesian Learning
ISI	Inter-Symbol Interferences
STBC	Space Time Block Coded
SAGE	Space-Alternating Generalized Expectation-Maximization
IFFT	Inverse Fast Fourier Transforms
CFO	Carrier Frequency Offset
JESBL	Joint Extended Sparse Bayesian Learning
NMSE	Normalised MSE
LS	Least Squares
DEBRE	Deterministic Blind Receiver
ACE	Adaptive Channel Estimation
SDNLMS	Sign Data Nlms
LMS	Least Mean Square
S-CFP	Simplified Closed-Form PARAFAC
SNR	Signal-To-Noise Ratio
CSI	Channel State Information
FDD	Frequency-Division Duplex
CE	Channel Estimation

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I. Introduction

For next-generation communications systems, a technology that combines OFDM and MIMO technologies is currently being researched as the most worthy prospect, spanning from wireless Systems to broadband access. Current researches have been focused on evaluating MIMO-OFDM systems in the existence of practical weaknesses like synchronization and CE errors [1][2][3]. In general, channel estimation is a key problem for MIMO-OFDM systems, particularly when multilevel modulation is used to obtain higher spectral efficiencies. As illustrated in Fig. 1, the typical method for CE is to determine how a physical channel could numerically impact an incoming signal, which is essentially an attempt to construct a mathematical model including all of the effects present throughout the communication medium [4] [5] [6].

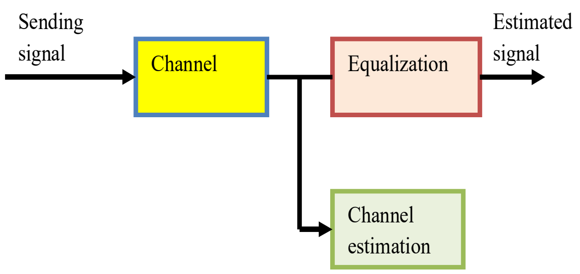

Fig. 1. The typical channel estimation model

The estimator concentrates on the system response to impulse excitation in the simplest situation, i.e., when a channel is a linear one [7]. However, the channel estimate is a sophisticated and extensive operation that takes into account a number of parameters. The first criteria are consistency, which represents the algorithm's potential to reduce the mean square estimated error. Furthermore, several essential components influence the sophistication and overhead that affect real-time performance [8] [9] [10]. These two criteria are typically mutually exclusive, i.e., the more precise the assessment, the more difficult the accompanying method; CE becomes a technique of experimenting with various algorithms to discover the perfect balancing point. Based on principle, CE algorithms are divided into three categories: 'non-blindness algorithms, blindness algorithms, and half-blindness algorithms' [11] [12]. For the pilot signal, the non-blindness method is the best-suited approach, as it relies on the transmitter's pilot signal, which is known by the receiver, to focus on CSI. Although there is a challenge with channel accommodation that is measured in bytes, the non-blindness method has been widely used in practice. The blindness algorithm, which is in contrast to the non-blindness method, is primarily based on the channel statistic's features, which are reliant on the inherent math information conveyed by the transmitted data rather than on any pilot signal. On the other hand, the half-blindness algorithm combines the benefits and drawbacks of both the non-blindness and blindness algorithms. When utilized for MIMO-OFDM systems, the non-blindness approach is simple and perhaps the most developed of the three methods discussed above. The LS, MMSE, and ML are the most common criteria to define the channel's current condition [13]. The optimum pilot sequence of MIMO-OFDM may be used to verify ML whether the channels with segmental fading are orthogonal to each other. It's indeed difficult to foresee the channel accurately using only a few pilot signals, mostly in cases where the optimal pilot sequence has been applied to the channel with segmented fading or ML is applied to the channel with continuous fading, demonstrating that CE accuracy is incompatible with spectrum efficiency.

The major contribution of this research work is:

- Undergoes a compact review on the recent CE algorithm for MIMO-OFDM systems
- The advantages and drawbacks of each of the collected research papers for review are furnished.
- The different methodologies and techniques adapted in each research paper are manifested.
- Performance-based comparative evaluation is undergone, and the best performance acquired is provided.
- The research gaps and challenges faced by the CE algorithm are portrayed, which could be a mile-stone for future researchers.

The rest of this paper is organized as: Section II discusses the recent works on CE algorithms/ techniques on MIMO-OFDM. Section III undergoes an Analysis of Collected research papers. The research gaps identified in CE algorithms employed for MIMO-OFDM are depicted in Section IV. This paper is concluded in Section V.

II. Literature Review

A. Related works

In 2020, Liao *et al.* [14] had introduced a DL-based CE algorithm for MIMO-OFDM with the intention of overcoming the high mobility issues faced by the MIMO-OFDM system. The CSI generated by the training samples was successfully used to adjust the parameters of rapid time-varying channels in highly mobile circumstances by applying offline training to the learning network. Compared to traditional methods, simulation findings demonstrated that the DL-based approach was more resilient for good mobility situations in MIMO-OFDM systems.

In 2019, Wang *et al.* [15] have presented a beam squint effect-aware CE technique for "FDD mmWave massive MIMO-OFDM systems with hybrid analog/digital precoding." The frequency-insensitive characteristics within each uplink channel route, including the AoA as well as time delay, were extracted using a compressive sensing-based methodology. In contrast, the complex channel gain, as well as frequency-sensitive parameter, has been extracted using a frequency-sensitive approach. Under generic system configurations in mmWave communications, numerical findings indicated that the suggested technique outperforms established approaches.

In 2019, Huang *et al.* [16] have introduced a NAMP methodology based on the LTE. Initially, NAMP doesn't require prior knowledge of the sparsity level. Second, to boost the signal reconstruction efficiency, a fixed step size has been determined. To avoid the less important atoms from being inserted, a Singular Entropy order determination method has been used. Furthermore, simulation results have been examined in-depth, demonstrating that perhaps the suggested technique required less computing complexity and, more importantly, provided more consistent results.

In 2020, Zhang, *et al.* [17] had proposed a unique channel estimating technique for STBC MIMO-OFDM systems that makes use of the time-varying wireless channel's intrinsic temporal correlation as well as sparsity. AMA and IMOT were two techniques used in the suggested method. First, an LGM model was used to determine the temporal correlation of the time-varying channel. The AMA method has been used to enhance the predicted CIR via noise reduction. The outcomes of simulations revealed that the optimal AMA-IMOT channel estimation technique outperforms comparative methods.

In 2018, Ma *et al.* [18] have proposed a new method for estimating channels for multi-antenna systems in high-mobility circumstances, including the high-speed train. To boost the modeling accuracy, the channel impulse response was typically separated into three domains. The genetic algorithm was then used to construct the architecture of structured CS and have recovered the channel using the pilot site that was optimized by the genetic algorithm. The simulation demonstrated that the developed methodology outperformed existing schemes in terms of recovery probability, MSE, and BER across a doubly selective channel with low computing cost.

In 2018, Qin *et al.* [19] have presented a new sparse CE technique that taken use of the delay domain's sparsity and the spatial domain's strong correlation. Researchers considerably minimized the number of coefficients to be approximated by using the BEM to characterize temporal variation as well as the G-SBEM to model spatial correlation. The efficacy of their proposed CE technique has been validated using simulation data. Researchers demonstrated that the proposed techniques have quite a considerably quicker convergence time when compared to other current methods.

In 2019, Kuai *et al.* [4] have used AFD and ADD probabilistic methods extensively to characterize the massive MIMO-OFDM channel. They have used the structured sparsity across the AFD and ADD of the channel to develop message-passing-based channel estimators with the STCS technique.

In 2019, Araújo *et al.* [7] have presented a tensor-based MMSE channel estimator that makes use of the frequency-selective massive MIMO channel's multidimensional structure in the frequency domain, providing a low-complexity option to vector-MMSE. This tensor-CS approach has been used to develop a T-OMP estimator to effectively solve a greedy constraint acquiring in each tensor dimension. The suggested channel estimator comes in two models: a joint search per tensor dimension or a sequential search that decreases the solution space as the tensor dimension grows.

In 2020, Mishra *et al.* [8] have proposed an SBL-based roughly sparse channel estimate method depending on trellis-based encoding and decoding for STTC MIMO-OFDM systems across the data subcarriers. First, using the MSBL architecture, a pilot-aided channel estimate technique was constructed. By explicitly addressing the influence of estimate errors, their theoretical definition conceptualized the performance of the suggested schemes in terms of the related FER upper limits.

In 2019, Lu *et al.* [11] have developed a hierarchical probabilistic model in large MIMO-OFDM systems using examining the precise physical structure of uplink channels in the delay-spatial domain. This was centered on DP before fitting the channel's structural sparse characteristics. The proposed CVBI-DP algorithm had considerably enhanced CE performance while reducing computational complexity and pilot overhead.

In 2018, Lin *et al.* [20] have improved the achievable CE performance by extending the AMP with the nearest neighbor pattern learning method, which dynamically recognizes and leverages the clustered structure throughout the 3-D virtual AOA-AOD-delay. The presented technique approaches the effectiveness constraint issued by the state evolution centered on the vector AMP paradigm. Their simulation findings demonstrated that it was preferable in mmWave systems with a wide frequency range.

In 2020, Lin *et al.* [21] In millimeter wave (mmWave), the authors have studied the CE problem with hybrid analog-digital architectures for MIMO-OFDM systems. In addition, they've projected a structured CP decomposition-based CE approach supplemented mostly by spatial smoothing method, wherein two programmable techniques featuring specific tensor modeling and parameter recovery procedures have been created, depending on the Vandermonde character of factor matrices. As this suggested method has involved ordinary linear algebra, it overcomes the risk of random initialization as well as the iterative operation.

In 2020, Kulsoom *et al.* [22] had projected a new framework for a multi-user large MIMO system based on FDD. The CSI was retrieved at the BS using suggested CS-based techniques after a "2-step quantization approach" was used at the UE. This data was further handed back to the BS, which recovers the CSI from restricted and quantized feedback using the suggested quantized partly joint Q-PJOMP or Q-PJIHT CS algorithms. SVD and MMSE beamforming using the predicted channel have been used in simulations.

In 2019, Akbarpour-Kasgari *et al.* [23] have suggested the StFBP method to exploit the simultaneous sparsity of mMIMO-OFDM channels. Researchers suggested gathering several excellent atoms for each step and using common sparsity throughout the system model, respectively, to enhance the convergence speed and estimation accuracy. Furthermore, by eliminating poor collected from previous atoms, the backward steps boost the precision. The suggested StFBP technique outperforms both the traditional CS-based as well as non-CS-based methods according to simulation findings.

In 2018, Mishra *et al.* [24] In an OSTBC, MIMO-OFDM wireless system, SBL-based techniques for roughly sparse CE had been described. A prototype approach for a scenario called ill-posed OSTBC MIMO-OFDM was presented using the parameterized prior-based SBL framework. The theoretical limitations demonstrate the effectiveness of the suggested approaches. Simulation data have been provided near the end.

In 2019, Jeya *et al.* [25] for MU-MIMO OFDM, an OSBS CE algorithm was suggested. Initially, QPSK modulation was used to modulate an incoming signal on the transmitting block. The PSA was then employed to mitigate the ISI. At each transmitter, an IFFT operation was used to map symbols. After that, they've to append AWGN to the symbols and send them to the receiver's antenna via the Multipath channel using the transmitter's antennas.

In 2019, Watanabe *et al.* [26] have considered the CE of systematic polar coded MIMO-OFDM, has proposed a modified pilot selection. For communication systems, they have achieved the theoretical limit using the Polar codes, and code-words were created by the systematic polar codes with the same information bit value. Moreover, they've projected an efficient CE scheme using this property.

In 2018, Hedayati *et al.* [27] had projected a novel semi-blind estimation model and symbol detection approach for STBC MIMO-OFDM systems depending upon the SAGE algorithm. The initial value was selected within the appropriate range in the SAGE algorithm for enhancing the convergence speed.

In 2018, Jomon *et al.* [28] have projected ESBL as a novel approach for CE in MIMO-OFDM, especially for multichannel compressive sensing. The estimation of the channels was accomplished via JESBL using the data as well as pilot subcarriers. In OFDM, the suggested approach had lessened the pilot subcarrier's count; in order to enhance the MIMO-OFDM system's spectral efficiency.

In 2021, Cheng *et al.* [29] have presented a joint time-variant CFO for channel selection in MIMO-OFDM systems. As per the maximum likelihood criterion, the authors have devised the joint estimator for the MIMO-OFDM system. Initially, using the derotation, the estimation of the initial CFO took place, and this was implied onto the frequency-domain equalizer. Further, to achieve a much significant CFO estimation, the authors have localized the fine frequency peak using the iterative method. The resultant of the proposed work had exhibited the supremacy of the projected work in terms of MSE performance.

B. Chronological Analysis

To make this compact review more significant, 20 most interesting research works on MIMO-OFDM CE models are collected. To grab more information regarding the recent works, this review has analyzed the papers published during the year 2018 to 2021. The chronological review of the collected research papers has been manifested in the bar chart illustrated in Fig. 2. In 2018, 6 research papers were collected, and it is contributed 30% to this survey. In addition, 40% (8 papers) and 25% (5 papers) of research papers have been collected in 2019 and 2020, respectively. The papers published in the year 2021 contributes 5% to this review

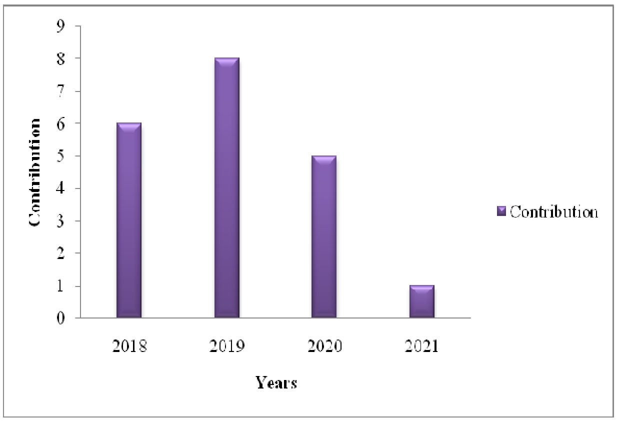

Fig. 2. Chronological Review

III. ANALYSIS ON COLLECTED RESEARCH PAPERS

In this research work, a literature review is conducted with 20 research papers collected from different international journals, published during different years (2018- 2020). Each model has its own set of benefits and downsides, which are listed in Table I. This might help future researchers acquire a thorough understanding of contemporary studies.

TABLE I. ADVANTAGES AND DRAWBACKS OF EXISTING CE MODELS

Author [citation]	**Adopted Methodology**	**Advantages**	**Drawbacks**
Liao *et al.* [14]	DL	✓ For high-mobility applications, it's quite durable. ✓ Better performance in terms of NMSE and BER	✓ In high-mobility situations, inability to adjust to channel changes. ✓ Resulting in the spread of errors
Wang *et al.* [15]	Hybrid analog/digital precoding	✓ Spectral efficiency has improved. ✓ With only a modest amount of training, can estimate and update channels	✓ Generates a significant disparity and severe imbalance in spectral efficiency across frequencies
Huang *et al.* [16]	NAMP algorithm	✓ Computational complexity is reduced ✓ Achieves more steady performance, especially in low SNR channel environments ✓ Increase the accuracy of the channel estimate	✓ The total running time is higher
Zhang, *et al.* [17]	STBC	✓ MSE is lower. ✓ Get rid of the noise impact ✓ The time-varying channel has the best TCSDR, BER, and NMSE performance, especially in low-to-medium SNR situations.	✓ Can't just turn off the noise at the noise-only taps
Ma *et al.* [18]	"adaptive support-aware block orthogonal matching"	✓ Recovery probability, MSE, and BER are all improved. ✓ Average computational complexity PAPR	✓ A shorter runtime ✓ A greater fluctuation power
Qin *et al.* [19]	G-SBEM	✓ Improve the recovery accuracy ✓ Reduce the measurement matrix's block-coherence	✓ Large error rate ✓ Higher computational complexity

		✓ Achieve better NMSE performance	
Kuai *et al.* [4]	Structured Turbo Compressed Sensing	✓ More rapid convergence ✓ Enhance competitive error performance across a variety of simulation scenarios	✓ For unknowns with clustered sparsity, this method does not perform well.
Araújo *et al.* [7]	Tensor-Based Channel Estimation	✓ Decreases the size of the search space in tensor dimensions ✓ A lesser level of complexity	✓ Lower convergence ✓ Lower ce accuracy
Mishra *et al.* [8]	"SBL-based approximately sparse channel estimation"	✓ Enhanced MSE and FER performance	✓ Exponentially increasing complexity
Lu *et al.* [11]	"Collapsed VBI-DP Based Structured Sparse Channel Estimation Algorithm"	✓ Can enhance channel estimate accuracy without adding to the computational complexity or pilot overhead.	✓ Higher MSE
Lin *et al.* [20]	AMP	✓ Less storage space is required ✓ A lesser level of complexity ✓ More closely describes the performance limit ✓ A shorter measurement period	✓ Higher nmse ✓ Lower convergence
Lin *et al.* [21]	Tensor-Based Channel Estimation	✓ Avoids the problem of random initialization ✓ Improves the accuracy of estimations ✓ Precision, robustness, and complexity have all improved. ✓ Delivers a high level of performance in terms of carrier frequency and bandwidth	✓ Higher time delay ✓ Higher computational complexity
Kulsoom *et al.* [22]	"Joint Sparse Channel Recovery with Quantized Feedback"	✓ Beamforming with the smallest MMSE ✓ Solving the overhead problem of training and feedback	✓ Higher complexity in terms of cost ✓ Need to reduce the computational resources and time
Akbarpour-Kasgari *et al.* [23]	Distributed Compressed Sensing	✓ More accuracy in channel estimation ✓ Increase the convergence rate ✓ Enhance the accuracy of the estimate	✓ Higher power consumption ✓ Lower spectral efficiency
Mishra *et al.* [24]	"SBL-Based Joint Sparse CE and Maximum Likelihood Symbol Detection"	✓ Performance with lower MSE and BER ✓ Reduce estimate errors in the channels ✓ A lesser level of complexity	✓ Higher sampling frequency ✓ Higher convergence errors ✓ Get trapped in local minima
Jeya *et al.* [25]	"Optimized semiblind sparse CE algorithm"	✓ In terms of BER, PSNR, SER, LS, and MMSE, it performs better.	✓ Higher execution time
Watanabe *et al.* [26]	Modified pilot selection	✓ Lower BER ✓ Consumes lower computational cost	✓ Higher coding rate
Hedayati *et al.* [27]	SAGE Algorithm	✓ Higher convergence rate ✓ Improved MSE and BER	✓ Might converge to a local minimum
Jomon *et al.* [28]	Distributed Compressive Sensing	✓ Minimize the amount of sub carriers for pilots ✓ Enhance spectral efficiency ✓ Increased convergence	✓ Higher computational complexity
Cheng *et al.* [29]	"Maximum likelihood-based adaptive iteration algorithm"	✓ Performance with lower bit error rate ✓ Offer high accuracy estimate ✓ Better trade-off ✓ Computational complexity is reduced	✓ Higher MSE

A. Recorded Performance

The performance of each of the research work collected for review as been identified, and recorded in Table II. The approach with least BER, MSE, and NMSE is said to be the best approach. In [14], the Time complexity has been recorded as $O(N_rN_tN^2)$. At N_t=8 and SNR=25, the Successful recovery probability is 1.0 in [19]. In [4], NMSE at N = 256 and SNR = 250 dB at Urban macro=-18 dB and Suburban macro=-18dB and Urban micro=-16dB. MSE for higher SNR in dB=30 is 10^{-5} in [4]. In [27], the Maximum delay has been recorded as 0.7 in [27]. In [11], the recorded Convergence at B_W = 20MHz, N_P = 64, I_P = 6, L = 64, SNR = 30dB is $10^{-4.2}$. Moreover, in [7], NMSE performances at SNR=40dB is -40dB. Moreover, at Doppler spread range= 300 Hz, the TCSDR performance for W = 1 is 0.985 in [17]. The SER analysis of the [21] at SNR =11 is 10^{-2}.

TABLE II. PERFORMANCE RECORDED

Author [citation]	**Recorded Performance**
Liao *et al.* [14]	standard deviation=0.3; Time complexity= $O(N_rN_tN^2)$;
Wang *et al.* [15]	At SNR=30db, the Spectral efficiency is 10bits/s/Hz
Huang *et al.* [16]	at SNR=30dB, the MSE=10^{-5} ; BER performance=10^{-2}; Running time=0.1s
Zhang, *et al.* [17]	at Doppler spread range= 300hz, the TCSDR performance for W = 1 is 0.985; TCDR performance at SNR=20 dB is 1;
Ma *et al.* [18]	average PAPR= 8.9751; MSE less than 0.5
Qin *et al.* [19]	At N_t=8 and SNR=25, the Successful recovery probability is 1.0 and NMSE performance=-28dB.
Kuai *et al.* [4]	NMSE at N = 256 and SNR = 250 dB at Urban macro=-18 dB and Suburban macro=-18dB and Urban micro=-16dB.
Araújo *et al.* [7]	NMSE performances at SNR=40dB is -40dB for K = 16; Spectral efficiency for 60 count of RF chains =9 (bps/Hz)
Mishra *et al.* [8]	MSE for SNR in dB=30 is 10^{-5}; FER for SNR in dB=0 is 10^{-5}
Lu *et al.* [11]	Convergence at B_W = 20MHz, N_P = 64, I_P = 6, L = 64, SNR = 30dB is $10^{-4.2}$. MSE performance at 150 bandwidth in MHz=$10^{-4.3}$.
Lin *et al.* [20]	NMSE [dB] at Measuring time duration (G)=1050 is -22; NMSE performance at 60^{th} Iteration times (T)=-23; NMSE performance at SNR=20dB is -28
Lin *et al.* [21]	NMSE performance at SNR=30dB is 10^{-4}; NMSE performance at 30^{th} transmitting surface is $10^{-4.2}$;
Kulsoom *et al.* [22]	Averaged SNR degradation for 120pilots=1; NMSE for 10^{th} Sc (Common Support)=10^{-4}; BER at SNR=30 is 10^{-}

	4.5.
Akbarpour-Kasgari *et al.* [23]	NMSE (dB) at 30th dB =-35dB; NMSE (dB) at 40 count of antenna=-32dB.
Mishra *et al.* [24]	MSE performance for M = 4-PSK; SNR=-0.3 for BER=10^{-2}
Jeya *et al.* [25]	BER performance at SNR =11 is $10^{-4.5}$dB, SER analysis at SNR =11 is 10^{-2}; LMSE at SNR =11 is$10^{0.05}$; Channel capacity at SNR =11 is $10^{0.05}$;
Watanabe *et al.* [26]	BER performance at SNR=10dB is10^{-5}dB
Hedayati *et al.* [27]	Maximum delay=0.7 µs; MSE at SNR=10dB is $10^{-4.5}$; BER at SNR=10dB is 10^{-6}
Jomon *et al.* [28]	BER at SNR=10dB is 10^{-2} ; MSE at SNR=10dB is $10^{-4.2}$;
Cheng *et al.* [29]	MSE at SNR=30dB is 10^{-6}; BER at SNR=30dB is 10^{-4}

B. Recorded Best Performance

A comparative evaluation has been made with the recorded performance of each of the research works, and the best outcome acquired is manifested in Table III. Among all the recorded performance, the best running time is recorded as 0.1s in [16]. Moreover, the approach that achieves the least MSE, as well as BER at the highest SNR, is said to be the best approach. At the highest SNR of 30dB, the Maximum likelihood-based adaptive iteration algorithm [29] has attained the best MSE value as 10^{-6} dB. In NMSE, the [21] has recorded the least value as 10^{-4} at SNR=30dB. The least MSE performance at 150 bandwidth in MHz=$10^{-4.3}$ in [11].

TABLE III. RECORDED BEST PERFORMANCE: A COMPARATIVE EVALUATION

Author [citation]	Recorded best Performance
Cheng *et al.* [29]	MSE at SNR=30dB is 10^{-6}
Huang *et al.* [16]	Running time=0.1s
Lin *et al.* [21]	NMSE performance at SNR=30dB is 10^{-4}
Lu *et al.* [11]	MSE performance at 150 bandwidth in MHz=$10^{-4.3}$.
Cheng *et al.* [29]	BER at SNR=30dB is 10^{-4}

IV. RESEARCH GAPS AND CHALLENGES

All over the globe, the wireless customers are increasing each day, and their seemingly "greedy" requests for high-data-rate services, radio spectrum are in expanding phase. The radio spectrum being a very rare and precious resource is ought to be utilized efficiently. So the modulated carriers must be positioned as close together as feasible without generating ICI. Moreover, it must be capable of carrying as many bits of information as much as possible. Because of its huge system capacity as well as fast data rates, and with less consumption of bandwidth and energy, the combination of MIMO and OFDM has emerged as one of the most viable broadband wireless access strategies. In MIMO-OFDM systems, the channels should first be correctly predicted, and then channel equalization has been used to acquire the broadcast signal. As a result, precise estimates of the changing channel impulse response are required [15] [18]. A precise estimation of the changing channel impulse response is required [15] [18]. To tackle the challenges of CE in MIMO-OFDM systems, several algorithms have been applied during the last few decades. The CE is grouped into two categories. The channel parameters can be estimated in one of the groups by transmitting a training sequence by introducing a known-to-the-receiver pilot structure. By repeating this procedure regularly, one could achieve ACE [19] [22]. The adaptive filter has been used to estimate channel information in linear CE techniques, and this is the other category. Linear CE methods, including LS techniques, are indeed very simple to implement because of their low computing complexity. Although the LMS algorithm has a low computing complexity, it performs poorly in terms of MSE [23]. Simplified LMS algorithms, such as the SDNLMS algorithm [24], could also be employed to lessen the LMS method's complexities. Compressive sensing has been frequently used in sparse CE techniques [25] [29]. These techniques, however, depend on the number of nonzero taps. Semi blind or blind CE [1] would be the last option. There is no necessity for training sequences or knowledge of noise statistics, and the channel impulse response may well be approximated only from the signals received. As a result of their enhanced spectral efficiency, blind CE techniques have received a lot of attention. The statistical characteristics of received signals are generally used in blind channel estimate methods; the channel is assumed to be unchanging during the reception phase. Conventional blind OFDM channel estimate algorithms aren't suited for online applications for the ACE mechanism. For dealing with the linear algebra of multiplexed arrays, parallel factor (PARAFAC) analysis has proven beneficial. PARAFAC has indeed been broadly applied for blind signal identification and parameter tuning in the realm of signal processing. For blind channel estimation, tensor decompositions have been employed in several recent researches. Although the TALS technique produces excellent MSE, it does have a large computational complexity and a sluggish convergence rate. The DEBRE technique converts the incoming signal into a 4-way tensor inside the frequency domain for MIMO-OFDM systems and then employs an ALS approach to determine the model's parameters. The DEBRE technique consumes a higher computational cost comparable to the TALS algorithm. Based on the tensor model for Tucker decomposition [9] [30], the LS-KRF and S-CFP algorithms produce an extremely comparable performance at high SNR circumstances despite added pilot overhead. The PARAFAC methods are suited for stationary channel environments. When the tensor model is deconstructed at each sample instant, the computing complexity becomes too high.

Moreover, there are some extant rapid adaptive PARAFAC decomposition methods. The MMSE-based approaches make use of second-order KCS and produce relatively close comparable results to the LS-based techniques [18]. They do, however, have the disadvantages of greater computing sophistication and the realistic lack of 2nd order channel statistics. The frequency-domain channel estimate methods based on LS are easy to use and do not require extra KCS. The optimization algorithms are indeed suggested as an optimal solution for enhancing the performance of CE algorithms, as they could enhance the convergence speed.

V. CONCLUSION

This paper has undergone a literature study of 20 distinct research works on channel estimation techniques of the MIMO-OFDM system. These papers were gathered from a variety of international publications published for several years (2018- 2020). The papers that were gathered were examined to determine their benefits and disadvantages. In addition, the recorded performance by each of the collected research work is manifested. Ultimately, the research gaps and challenges faced by the recent literature were addressed to guide future research works.

References

[1] S. Wu, H. Yao, C. Jiang, X. Chen, L. Kuang and L. Hanzo, "Downlink Channel Estimation for Massive MIMO Systems Relying on Vector Approximate Message Passing," IEEE *Transactions on Vehicular Technology*, vol. 68, no. 5, pp. 5145-5148, May 2019.doi: 10.1109/TVT.2019.2904405

[2] Y. Sui, Y. He, T. Cheng, Y. Huang and S. Ning, "Broad Echo State Network for Channel Prediction in MIMO-OFDM Systems," IEEE *Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 13383-13399, Nov. 2020. doi: 10.1109/TVT.2020.3025913

[3] W. Ji, C. Ren and L. Qiu, "Common Sparsity and Cluster Structure Based Channel Estimation for Downlink Massive MIMO-OFDM Systems," IEEE *Signal Processing Letters*, vol. 26, no. 1, pp. 59-63, Jan. 2019. doi: 10.1109/LSP.2018.2878617

[4] X. Kuai, L. Chen, X. Yuan and A. Liu, "Structured Turbo Compressed Sensing for Downlink Massive MIMO-OFDM Channel Estimation," IEEE *Transactions on Wireless Communications*, vol. 18, no. 8, pp. 3813-3826, Aug. 2019. doi: 10.1109/TWC.2019.2917905

[5] G. Wunder, S. Stefanatos, A. Flinth, I. Roth and G. Caire, "Low-Overhead Hierarchically-Sparse Channel Estimation for Multiuser Wideband Massive MIMO," IEEE *Transactions on Wireless Communications*, vol. 18, no. 4, pp. 2186-2199, April 2019.

[6] R. Tian, Z. Wang and X. Tan, "A New Leakage-Based Precoding Scheme in IoT Oriented Cognitive MIMO-OFDM Systems," IEEE *Access*, vol. 6, pp. 41023-41033, doi: 10.1109/ACCESS.2018.2859265

[7] D. C. Araújo, A. L. F. de Almeida, J. P. C. L. Da Costa and R. T. de Sousa, "Tensor-Based Channel Estimation for Massive MIMO-OFDM Systems," IEEE *Access*, vol. 7, pp. 42133-42147, 2019. doi: 10.1109/ACCESS.2019.2908207

[8] A. Mishra, A. K. Jagannatham and L. Hanzo, "Sparse Bayesian Learning-Aided Joint Sparse Channel Estimation and ML Sequence Detection in Space-Time Trellis Coded MIMO-OFDM Systems," IEEE *Transactions on Communications*, vol. 68, no. 2, pp. 1132-1145, Feb. 2020. doi: 10.1109/TCOMM.2019.2953260

[9] P. Priya and D. Sen, "Data Detection With CFO Uncertainty and Nonlinearity for mmWave MIMO-OFDM Systems," IEEE *Systems Journal*. doi: 10.1109/JSYST.2021.3093333

[10] X. Cheng, K. Xu and S. Li, "Compensation of Phase Noise in Uplink Massive MIMO OFDM Systems," IEEE *Transactions on Wireless Communications*, vol. 18, no. 3, pp. 1764-1778, March 2019. doi: 10.1109/TWC.2019.2897089

[11] X. Lu, C. N. Manchón and Z. Wang, "Collapsed VBI-DP Based Structured Sparse Channel Estimation Algorithm for Massive MIMO-OFDM," IEEE *Access*, vol. 7, pp. 16665-16674, 2019. doi: 10.1109/ACCESS.2019.2896125

[12] K. P. Rajput, M. F. Ahmed, N. K. D. Venkategowda, A. K. Jagannatham, G. Sharma and L. Hanzo, "Robust Decentralized and Distributed Estimation of a Correlated Parameter Vector in MIMO-OFDM Wireless Sensor Networks," IEEE *Transactions on Communications*.
doi: 10.1109/TCOMM.2021.3092409

[13] H. He, C. Wen and S. Jin, "Bayesian Optimal Data Detector for Hybrid mmWave MIMO-OFDM Systems With Low-Resolution ADCs," IEEE *Journal of Selected Topics in Signal Processing*, vol. 12, no. 3, pp. 469-483, June 2018. doi: 10.1109/JSTSP.2018.2818063

[14] Y. Liao, Y. Hua and Y. Cai, "Deep Learning Based Channel Estimation Algorithm for Fast Time-Varying MIMO-OFDM Systems," IEEE *Communications Letters*, vol. 24, no. 3, pp. 572-576, March 2020. doi: 10.1109/LCOMM.2019.2960242

[15] B. Wang, M. Jian, F. Gao, G. Y. Li and H. Lin, "Beam Squint and Channel Estimation for Wideband mmWave Massive MIMO-OFDM Systems," IEEE *Transactions on Signal Processing*, vol. 67, no. 23, pp. 5893-5908, 1 Dec.1, 2019. doi: 10.1109/TSP.2019.2949502

[16] Y. Huang, Y. He, Q. Luo, L. Shi and Y. Wu, "Channel Estimation in MIMO–OFDM Systems Based on a New Adaptive Greedy Algorithm," IEEE *Wireless Communications Letters*, vol. 8, no. 1, pp. 29-32, Feb. 2019. doi: 10.1109/LWC.2018.2848916

[17] M. Zhang, X. Zhou and C. Wang, "Time-Varying Sparse Channel Estimation Based on Adaptive Average and MSE Optimal Threshold in STBC MIMO-OFDM Systems," IEEE *Access*, vol. 8, pp. 177874-177895, 2020. doi: 10.1109/ACCESS.2020.3026210

[18] X. Ma, F. Yang, S. Liu, J. Song and Z. Han, "Sparse Channel Estimation for MIMO-OFDM Systems in High-Mobility Situations," IEEE *Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6113-6124, July 2018. doi: 10.1109/TVT.2018.2811368

[19] Q. Qin, L. Gui, B. Gong and S. Luo, "Sparse Channel Estimation for Massive MIMO-OFDM Systems Over Time-Varying Channels," IEEE *Access*, vol. 6, pp. 33740-33751, 2018. doi: 10.1109/ACCESS.2018.2843783

[20] X. Lin, S. Wu, C. Jiang, L. Kuang, J. Yan and L. Hanzo, "Estimation of Broadband Multiuser Millimeter Wave Massive MIMO-OFDM Channels by Exploiting Their Sparse Structure," IEEE *Transactions on Wireless Communications*, vol. 17, no. 6, pp. 3959-3973, June 2018. doi: 10.1109/TWC.2018.2818142

[21] Y. Lin, S. Jin, M. Matthaiou and X. You, "Tensor-Based Channel Estimation for Millimeter Wave MIMO-OFDM With Dual-Wideband Effects," IEEE *Transactions on Communications*, vol. 68, no. 7, pp. 4218-4232, July 2020. doi: 10.1109/TCOMM.2020.2983673

[22] F. Kulsoom, A. Vizziello, H. N. Chaudhry and P. Savazzi, "Joint Sparse Channel Recovery With Quantized Feedback for Multi-User Massive MIMO Systems," IEEE *Access*, vol. 8, pp. 11046-11060, 2020. doi: 10.1109/ACCESS.2020.2965280

[23] A. Akbarpour-Kasgari and M. Ardebilipour, "Massive MIMO-OFDM Channel Estimation via Distributed Compressed Sensing," IEEE *Wireless Communications Letters*, vol. 8, no. 2, pp. 376-379, April 2019. doi: 10.1109/LWC.2018.2873339

[24] A. Mishra, N. S. Yashaswini and A. K. Jagannatham, "SBL-Based Joint Sparse Channel Estimation and Maximum Likelihood Symbol Detection in OSTBC MIMO-OFDM Systems," IEEE *Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4220-4232, May 2018. doi: 10.1109/TVT.2018.2793221

[25] R. Jeya, B. Amutha,"Optimized semiblind sparse channel estimation algorithm for MU-MIMO OFDM system", Computer Communications, Vol.146, 2019

[26] K.Watanabe, S. Kojima, T. Akao, M. Katsuno, K. Maruta, C.-J. Ahn,"Modified pilot selection for channel estimation of systematic polar coded MIMO-OFDM", 2019

[27] M. K. Hedayati, H. Bakhshi, M. Cheraghi, "SAGE Algorithm for Semi-Blind Channel Estimation and Symbol Detection for STBC MIMO OFDM Systems", Wireless Pers Commun, 2018

[28] K. Charly Jomon1 and S. Prasanth,"Joint Channel Estimation and Data Detection in MIMO-OFDM Using Distributed Compressive Sensing", Radioelectronics and Communications Systems, 2018

[29] N.-H. Cheng, K.-C. Huang, Y.-F. Chen and S.-M. Tseng,"Maximum likelihood-based adaptive iteration algorithm design for joint CFO and channel estimation in MIMO-OFDM systems", EURASIP Journal on Advances in Signal Processing, 2021

[30] P. Singh, H. B. Mishra, A. K. Jagannatham and K. Vasudevan, "Semi-Blind, Training, and Data-Aided Channel Estimation Schemes for MIMO-FBMC-OQAM Systems," IEEE Transactions on Signal Processing, vol. 67, no. 18, pp. 4668-4682, 15 Sept.15, 2019, doi: 10.1109/TSP.2019.2925607.