MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 697-702

Hybrid Model for Efficient Channel Estimation in 5G Multicarrier Modulation using OMP

Guntukala Surendher[1], Tipparti Anil Kumar[2], Dhiraj Sunehra[3]
[1] Research Scholar, JNTUH, Dept. of ECE,
NGIT, Hyderabad, Telangana, India, (8 pt)
[2] professor, Dept. of ECE, Jyothishmathi Institute of Technology, Karimnagar
[3] Professor, Dept of ECE, JNTUH University College of Engineering, Rajanna Siricilla

Article Info

Article history:
Received month dd, yyyy
Revised month dd, yyyy
Accepted month dd, yyyy

Keywords:
5G network
Channel Estimation
MIMO
OFDM
SNR
OMP

ABSTRACT

Channel estimation is fundamental to efficiently operating multi-input, multi-output (MIMO) devices in 5G networks. This work presents a hybrid optimal channel estimation model to improve the accuracy and efficiency of channel estimation in 5G networks by combining the advantages of orthogonal frequency division multiplexing (OFDM) and filter bank multicarrier (FBMC). Using sophisticated sparse signal recovery techniques such as orthogonal matching pursuit (OMP), the proposed model correctly estimates the channel over multiple signal-to-noise ratios. The main performance metrics investigated in the model evaluation process are mean square error (MSE), bit error rate (BER), spectral efficiency, channel capacity, and throughput. Instead of traditional OFDM, 5G networks use the hybrid-optimal model at high SNR levels to improve channel prediction accuracy and data transmission efficiency.

Corresponding Author:
Guntukala Surendher, Research Scholar, JNTUH, Dept. of ECE,
NGIT, Hyderabad, Telangana, India, surendher.g@gmail.com
ORCID id: 0009-0007-8350-6427

1. INTRODUCTION

Accurate channel prediction is crucial to improve wireless communication systems and meet the needs for fast, consistent, and low-latency connectivity of 5G networks [1]. The inherent limitations of 5G networks make the exact reconstruction of real-time communication channels dependent on channel estimate techniques. Among these constraints are managing vast volumes of data, working across several frequency ranges, and keeping a sizable networked device count [2]. Precise channel forecasts help to ascertain how much MIMO [4] and OFDM technologies of 5G enhance system performance, reduce transmission mistakes, or boost data capacity.

Conventional channel estimate methods, OFDM [3], and 4G LTE cannot satisfy 5G's higher data volume and lower latency requirements than those of 4G LTE. In OFDM, cyclic prefixes lower inter symbol interference even with possible spectrum inefficiencies and performance degradation [5]. The channel estimation suffers from non-orthogonality of the subcarriers. For 5G, cyclic prefixes are essential because of their enhanced spectrum efficiency in Filter Bank Multicarrier (FBMC) technology [6]. Hybrid solutions are necessary to combine the benefits of modern technology with its inherent limitations to manage the complex and sometimes contradictory strategies defining 5G installations [7].

For optimal channel estimation, we present a hybrid approach combining the benefits of OFDM and FBMC. By using sparse signal recovery methods more significantly, the Orthogonal Matching Pursuit (OMP) model increases the spectral efficiency of Filter Bank Multicarrier (FBMC) and the robustness of Orthogonal Frequency Division Multiplexing (OFDM) in dynamic multi-user environments by improving estimate accuracy in sparse channels. This hybrid method maximizes channel predictions over several signal-to-noise ratios, improving general system efficiency.

The paper is organized as follows: Section II discusses the various channel estimation techniques. Section III presents the proposed hybrid channel estimation model, while Section IV provides performance analysis and comparative results. Finally, Section V concludes the paper with insights into future applications of the hybrid model in 5G networks.

II. RELATED WORK

The increasing demand for reliable, high-capacity wireless access has accelerated the rapid development of 5G communications. The authors of [8] proposed effective deep learning approaches for 5G communication applications. This article analyzes the basic concepts of various prominent deep-learning communication systems, highlighting their limitations and future avenues for further research. The author of [9] developed a revolutionary training-free deep learning algorithm for channel estimation in high-dimensional communication data. A deep neural network designed to generate a signal from a low-noise input can adjust its parameters through the deep channel estimator. The resulting signal is partitioned into prototype symbols by approximating the least squares to facilitate channel estimation.

The authors of [10] used advanced deep learning approaches to address nonlinear distortion and interference in OFDM systems while investigating frequency-selective wireless channel characteristics. Unlike traditional OFDM receivers, the proposed DL technique directly captures transmitted symbols while indirectly estimating channel state information. A deep learning approach, developed initially to correct channel distortion with simulated data derived from channel characteristics, facilitates real-time recovery of streamed data.

The authors present a deep neural network approach for identifying doubly selective channels [11]. The quantitative results show that the new method outperforms the previous estimator regarding efficiency and robustness while accounting for temporal instability in the channel data. A deep learning-based channel estimation method was used to fully reconstruct the channel state using pilot data that included a two-dimensional image of the time-frequency response of the fading channel, image super-resolution, and a denoising image restoration technique [12].

Akbarpour-Kasgari and Ardebilipour [13] introduced a distributed compressed sensing method for channel estimation in extensive MIMO systems. The Stage-Wise Forward-Backward-Pursuit (StFBP) approach helps to solve this challenge. This method combines the sparsity of OFDM and mMIMO channels to increase the estimation accuracy and convergence speed. The general sparsity of the system model allows many excellent atoms to be included at each operational level. Reducing the number of erroneous atoms once acquired helps to increase the accuracy. This work aims to evaluate the performance of the MATLAB simulation tool. Comparative simulation results of channel estimation using an Auxiliary Information-based Block Subspace Pursuit approach are obtained [14].

This is an adaptive greedy channel estimation method [15] for MIMO systems. Compressed sensing is combined with the New Adaptive Matching Pursuit (NAMP) method in this system. By selecting atoms with constant step sizes, removing low-energy components from the sparse solution, and finding a unique entropy order, efficiency is increased, and computational complexity is reduced. The MATLAB simulation tool made it easier to evaluate the efficiency of the approach. The SAMP approach helps to analyze NAMP activities better. MIMO systems are more efficient, according to simulation research.

Anil Kumar and Anjaneyulu [16] used M-estimators to develop a channel estimation method for multicarrier 5G wireless communication systems. One method juxtaposes M-estimator simulation results with LS and MMSE estimates to demonstrate superior performance efficiency in SNR. Jiguang et al. [17]

introduced a two-phase channel estimation method for a millimeter-wave (mmWave) MIMO system enhanced by a reconfigurable intelligent surface. The objective is to illustrate a technique that shows how the two-phase channel estimation strategy improves the signal-to-noise ratio performance.

This study [18] evaluates the effectiveness of a Discrete Fourier Transform (DFT) channel estimation method in a Fifth Generation (5G) OFDM waveform within an IRS-assisted communication framework. The full OFDM signal is not required for pilot transmission, as DFT-based channel estimation facilitates simultaneous data transmission. The effects of the number of resource elements, the sparsity of the training sequence, and the multipath delay spread within the OFDM symbol are analyzed at various SNR levels, both with and without direct link. The results show that the delay spread significantly affects the performance and that the training sequence length can be reduced.

Chimp-based CatBoost Channel Estimation (CbCBCE) [19], represents an innovative hybrid methodology that integrates the CatBoost algorithm with the Chimp optimization method. The Chimp approach evaluates channel parameters and then facilitates their improvement. The case study finally confirms the proposed paradigm. The results of the proposed model were assessed and contrasted with those of conventional methods. The proposed method outperforms conventional techniques.

This paper [20] investigates the increasing demand for accurate wireless channel estimation (WCE) in current wireless technologies such as 5G and future developments. We first used independent and identically distributed Gaussian random processes to characterize the wireless channel between a transmitter and multiple receivers with different antennas. We evaluated transmission angles and channel strengths over the Earth's azimuth. We then use a Simple Random Estimation (SRE) technique to investigate the identical radio channel at the transmitter. Our numerical results indicate that while WCE remains generally stable, channel intensities and orientations exhibit significant variations. Devices and users experience degraded quality of service (QoS) and data loss due to estimation errors at the transmitter.

III. PROPOSED MODEL

Decoding transmitted signals in 5G wireless communication networks using orthogonal frequency division multiplexing (OFDM) MIMO technology through channel estimation. Figure 1 illustrates the proposed model functionality. Channel estimation involves determining the channel matrix H that characterizes signal transmissions in a multipath fading environment from Nt transmit antennas to Nr receive antennas. An accurate understanding of the channel matrix is essential for equalization, data demodulation, and decoding at the receiver. In OFDM systems, pilot symbols, which divide the transmission into numerous orthogonal subcarriers, are assigned to specific subcarriers called pilot subcarriers. The received signal Y consists of additive Gaussian noise N, the transmitted signal P, and the channel matrix H. The estimation technique uses the known pilot signals, P, in conjunction with the received signal, Y, to derive H and mitigate the influence of the noise, N.

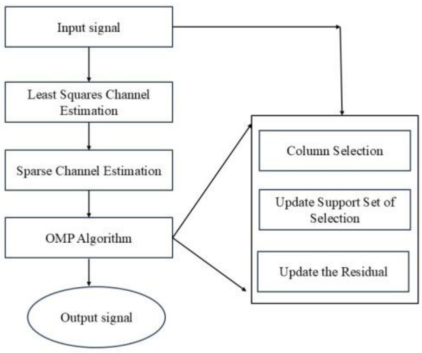

Figure 1: Proposed model flow diagram

The following matrix equation gives the received signal model:

$$Y = PH + N$$

Where:

- $Y \in C^{N_p X N_r}$, received signal matrix.
- $P \in C^{N_p X N_t}$, pilot matrix.
- $H \in C^{N_t X N_r}$, channel matrix.
- $N \in C^{N_p X N_r}$, noise matrix.

3.1 Least Squares (LS) Channel Estimation

Least-squares (LS) estimation is typically used in 5G networks to approximate the channel. Standardized pilot symbols minimize the squared difference between the expected and actual signals. The degree of LS independence is affected by noise or channel variables. Sensitivity to external interference increases as the signal-to-noise ratio decreases. Least squares is a computationally simple, efficient, and practical method.

Using pilot symbols, the LS approach minimizes the squared error between the expected and actual signals. The LS channel estimate $\widehat{H}_{LS}$ is given by:

$$\widehat{H}_{LS} = (P^H P)^{-1} P^H Y$$

Where,

P^H is the conjugate transpose (Hermitian) of the pilot matrix P.

$(P^H P)^{-1}$ is the inverse of the matrix.

Minimum Mean Square Error (MMSE) Channel Estimation

The advanced Minimum Mean Square Error (MMSE) estimation technique uses historical data on noise variability and channel characteristics. The mean square error between the actual and expected channels is reduced by incorporating noise characteristics and channel autocorrelation. LMSE produces inferior channel predictions compared to MMSE under noisy conditions. Although it is more computationally intensive and requires understanding the channel data, it is better suited to scenarios where efficiency is preferred over complexity.

$$\widehat{H}_{MMSE} = R_H P^H (P R_H P^H + \sigma^2 I)^{-1} Y$$

Where,

R_H is the autocorrelation matrix of the channel.

σ^2 is the noise variance.

I is the identity matrix.

$\widehat{H}_{MMSE}$ is the MMSE estimate of the channel matrix.

3.2 Compressed Sensing for Sparse Channel Estimation in 5G Systems

Compressed sensing (CS) provides an effective framework for predicting sparse signals from a limited data set. In the sparse channel model of 5G wireless communications, only a limited number of propagation channels are meaningful, resulting in most channel coefficients being either negligible or non-existent. Reducing the number of pilot symbols improves compressed sensing methods, thereby increasing spectral efficiency and reducing channel estimation complexity. The limited number of essential propagation paths between the transmitter and receiver in large MIMO systems results in sporadic sparse channels in 5G networks. Compressed sensing efficiently manages sparse channels by limiting the input related to unknown variables and solving an underdetermined linear

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 697-702

equation system.The sparse channel matrix of 5G systems, characterized by a limited number of significant non-zero components, is used in the sparsity-based optimization problem within compressed sensing. The objective is to reconstruct the sparse channel matrix H given a limited set of incoming pilot symbols Y. This problem can be characterized as an optimization problem aimed at minimizing the l_1 norm of the channel matrix to improve sparsity and ensure a close match between the expected and observed signal.

$$\hat{H} = \arg\min_{H} \|H\|_1 \text{subject to} \|Y - PH\|_2^2 \leq \epsilon$$

$\|H\|_1$ is the l_1-norm of H, which promotes sparsity by minimizing the sum of the absolute values of the channel coefficients,

$\|Y - PH\|_2^2$ is the l_2-norm, ensuring the received signal Y and predicted signal PH are close, with an error tolerance ϵ accounting for noise.

The l_1 norm represents sparsity more effectively than the l_2 norm, which is commonly used to allocate energy among multiple coefficients. Solving this convex optimization problem requires accurate channel estimation, which requires a limited amount of data with appropriate non-zero channel components. This method is used in large-scale MIMO systems within 5G, incredibly when pilot resources are limited.

3.3 Recovery Using Orthogonal Matching Pursuit (OMP)

Orthogonal Matching Pursuit (OMP) is a widely used greedy algorithm to recover sparse vectors from underdetermined linear systems in compressed sensing, especially in sparse channel estimation. The initial phase in the iterative development of the sparse channel matrix involves identifying the most significant columns in the measurement (or pilot) matrix that correspond to the residual signal at each level.The channel matrix H in 5G MIMO OFDM systems is sparse due to limited multipath propagation at millimeter-wave frequencies and large MIMO channels. Orthogonal matching pursuit (OMP) is used in sparse channel estimation techniques. By carefully selecting the most significant columns of the pilot matrix P to construct the sparse channel vector H, OMP uses fewer inputs than conventional methods such as LS or MMSE.Orthogonal Matching Pursuit is a valuable method to address the optimization challenges of sparsity in channel estimation. It also reduces the number of non-zero components in the solution while accurately capturing the input signal. These components improve processing and optimize pilot signals, making them essential for 5G systems with large antenna arrays and high data rates. OMP improves computational efficiency by avoiding complex methods such as L1 minimization (basis pursuit) and the need to solve a convex optimization problem using a greedy approach for sparse channel recovery.

OMP Algorithm
Input:
$P \in C^{N_p X N_t}$
$Y \in C^{N_p X N_r}$
Begin ()
r_0=Y
s=∅
k=0
for each i
    $Column\ Selection: i_k = \arg\min_{H} |P^H r_k|$
    $Update\ Support\ Set: S \leftarrow S \cup \{r_k\}$
End for
$\text{Least} - \text{squares Computation}: x_S = \arg\min_{x} \|Y - P_{Sx}\|_2^2$
$Update\ the\ Residual: r_k \leftarrow Y - P_{SxS}$
End

IV. RESULTS AND DISCUSSION

The performance of the proposed model is evaluated in terms of symbol error rate, signal-to-noise ratio, bit error rate, mean square error, channel capacity, throughput, and spectral efficiency. Figure 2 shows that Facebook MCMC, OFDM, and the hybrid optimal model consistently exhibit the lowest symbol error rate at all SNR levels. At a signal-to-noise ratio of 0 dB, the proposed model achieves a symbol error rate of 0.18, while FBMC and OFDM yield rates of 0.22 and 0.25, respectively. At a signal-to-noise ratio (SNR) of 20 dB, the proposed model exhibits a symbol error rate (SER) of 0.0005. The symbol error rates of FBMC and OFDM are significantly different, recorded at 0.008 and 0.001, respectively. The proposed technique shows a 30 dB improvement over FBMC, which is 0.00002, and OFDM is 0.00004, achieving a symbol error rate of 0.00001. With its excellent error reduction capabilities, the proposed model is particularly beneficial for 5G networks under high SNR conditions.

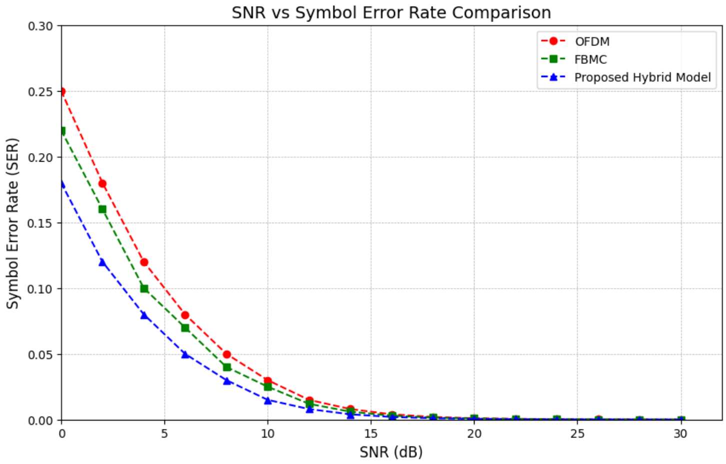

Figure 2: Comparison of SNR and SER

As shown in Figure 3, OFDM and the proposed hybrid model, FBMC, have the lowest BERs at all signal-to-noise ratio levels. Compared to the BERs of 0.10 for FBMC and 0.12 for OFDM, the proposed model's BER of 0.08 at 0 dB SNR is significantly higher. With a 30 dB SNR and a low BER of 0.00005, the proposed model performs better than Filter Bank Multicarrier (0.00008) and Orthogonal Frequency Division Multiplexing (0.0001). This illustrates how the proposed approach improves error performance and noise immunity, enabling reliable communications in 5G networks.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 697-702

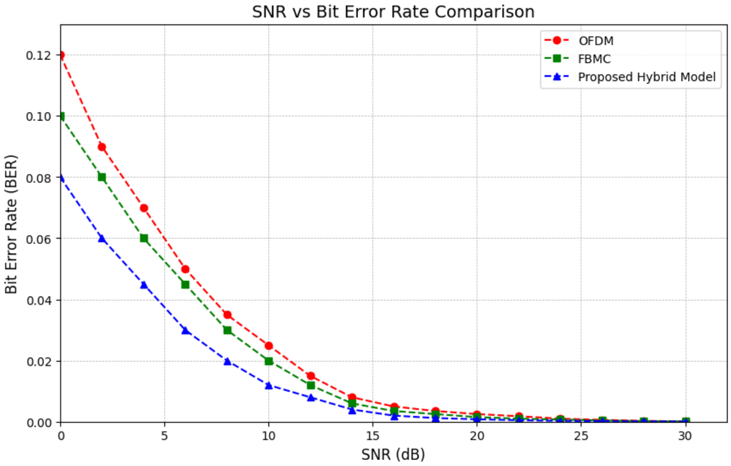

Figure 3: Comparison of SNR and BER

As shown in Figure 4, the proposed hybrid model consistently outperforms OFDM, FBMC, and the other techniques in terms of MSE and SNR. As a result, the channel estimation is likely to be more accurate. When the signal-to-noise ratio is 0 dB, the mean square errors of OFDM and Facebook MC are both 0.10. As a result, the mean square error of the proposed model is much lower. With an MSE of 0.002 and an FBMC of 0.0003 at 30 dB SNR, the proposed approach outperforms OFDM. The proposed hybrid approach shows that channel estimation in 5G networks becomes more accurate and economic as the SNR level increases.

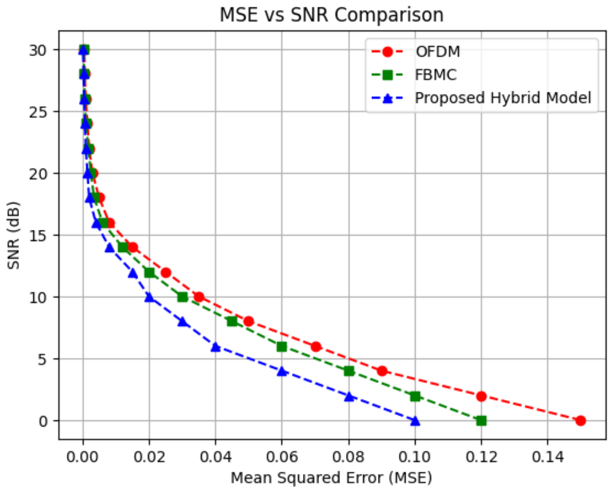

Figure 4: Comparison of SNR and MSE

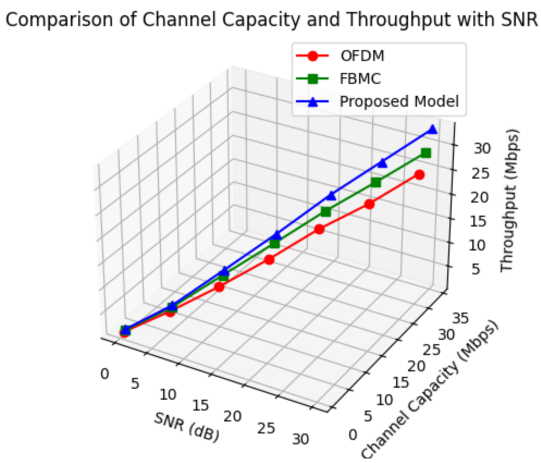

Figure 5: Comparison of SNR, Channel Capacity, and Throughput

The performance variations at certain SNR levels can be evaluated using the throughput and channel capacity studies shown in Figure 5 for OFDM, FBMC, and the proposed hybrid model. Although the OFDM and FBMC algorithms provide 0.8 Mbps and 1.0 Mbps, the proposed hybrid method achieves 1.1 Mbps at 0 dB SNR. The reduction in performance is achieved in part by a higher signal-to-noise ratio. With a 10 dB SNR throughput of 11.0 Mbps, the recommended approach beats OFDM's 8.5 Mbps and FBMC's 10.2 Mbps. Although OFDM and Facebook MC achieve throughputs of 18 Mbps and 20.5 Mbps, the proposed hybrid architecture achieves a throughput of 22.9 Mbps at 20 dB SNR. Although Facebook MC and OFDM have throughputs of 30.1 Mbps and 27 Mbps, the proposed method offers a throughput of 33.7 Mbps at 30 dB SNR. The results show that the proposed hybrid model maximizes the given channel capacity, especially at high SNR levels.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 697-702

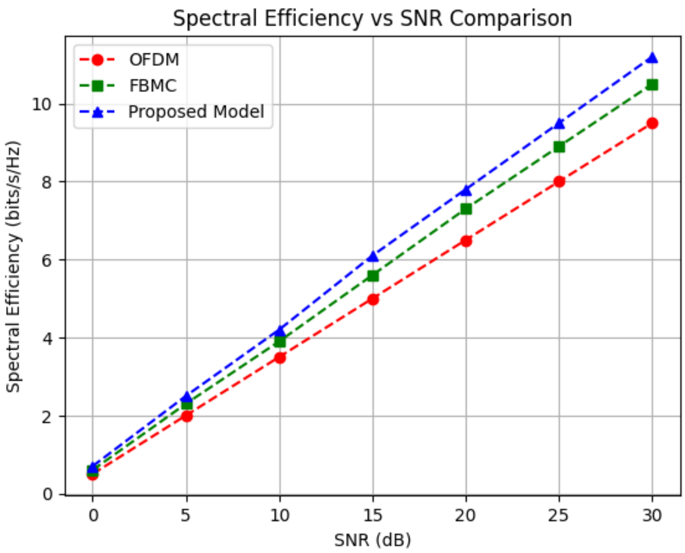

Figure 6: Comparison of SNR and Spectral efficiency

OFDM consistently surpasses both FBMC and TDM across all SNR levels, as demonstrated by the hybrid model's spectral efficiency and SNR analysis in Figure 6. The hybrid model proposed in this study surpasses the 0.5 bits/s/Hz of OFDM and the 0.6 bits/s/Hz of FBMC, attaining a spectral efficiency of 0.7 bits/s/Hz at low SNR (e.g., 0 dB). The suggested model's performance is enhanced with rising SNR; at 30 dB, it attains 11.2 bits/s/Hz, representing a 17.9% improvement over OFDM and a 6.7% enhancement over FBMC. The principal objective of 5G networks is to enhance throughput, and our ongoing research indicates that the suggested method effectively optimizes the available spectrum under high-SNR conditions.

V. CONCLUSION

This study proposes a hybrid optimal channel estimation model to overcome the limitations of both OFDM, which is constrained by cyclic prefix overhead, and FBMC, which is hampered by orthogonality issues. Orthogonal Matching Pursuit (OMP) and alternative sparse channel estimation techniques improve the channel prediction accuracy of the proposed model for 5G MIMO systems at elevated signal-to-noise ratios. The hybrid model outperforms both OFDM and FBMC at all SNR levels, as assessed by performance metrics such as BER, SNR, channel capacity, throughput, and spectral efficiency. The approach outperforms OFDM and FBMC regarding spectral efficiency (11.2 bits/s/Hz) and throughput (33.7 Mbps at 30 dB SNR). Applications such as enhanced mobile broadband and ultra-reliable low-latency communications require reduced latency, improved throughput, and increased spectrum efficiency, making the hybrid architecture suitable for 5G networks. The results show that systematic and consistent channel prediction improves the overall efficiency of 5G systems.

FUNDING INFORMATION
Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Guntukala Surendher	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Tipparti Anil Kumar		✓				✓			✓	✓		✓		
Dhiraj Sunehra			✓	✓	✓	✓			✓		✓			

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1]. Gupta A, Jha RK. A survey of 5G network: Architecture and emerging technologies. IEEE access. 2015 Jul 28;3:1206-32.
[2]. Apelfröjd R. *Channel estimation and prediction for 5G applications* (Doctoral dissertation, Acta Universitatis Upsaliensis).
[3]. Hwang T, Yang C, Wu G, Li S, Li GY. OFDM and its wireless applications: A survey. IEEE transactions on Vehicular Technology. 2008 Aug 26;58(4):1673-94.
[4]. Lu L, Li GY, Swindlehurst AL, Ashikhmin A, Zhang R. An overview of massive MIMO: Benefits and challenges. IEEE journal of selected topics in signal processing. 2014 Apr 15;8(5):742-58.
[5]. Stuber GL, Barry JR, Mclaughlin SW, Li Y, Ingram MA, Pratt TG. Broadband MIMO-OFDM wireless communications. Proceedings of the IEEE. 2004 Feb 29;92(2):271-94.
[6]. Schellmann M, Zhao Z, Lin H, Siohan P, Rajatheva N, Luecken V, Ishaque A. FBMC-based air interface for 5G mobile: Challenges and proposed solutions. In2014 9Th international conference on cognitive radio oriented wireless networks and communications (CROWNCOM) 2014 Jun 2 (pp. 102-107). IEEE.
[7]. Pourkabirian A, Anisi MH. Robust channel estimation in multiuser downlink 5G systems under channel uncertainties. IEEE Transactions on Mobile Computing. 2021 May 27;21(12):4569-82.
[8]. Huang H, Guo S, Gui G, Yang Z, Zhang J, Sari H, Adachi F. Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions. IEEE Wireless Communications. 2019 Aug 5;27(1):214-22.
[9]. Balevi E, Andrews JG. Deep learning-based channel estimation for high-dimensional signals. arXiv preprint arXiv:1904.09346. 2019 Apr 19.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 697-702

[10]. Ye H, Li GY, Juang BH. Power of deep learning for channel estimation and signal detection in OFDM systems. IEEE Wireless Communications Letters. 2017 Sep 28;7(1):114-7.
[11]. Liao Y, Hua Y, Cai Y. Deep learning based channel estimation algorithm for fast time-varying MIMO-OFDM systems. IEEE Communications Letters. 2019 Dec 16;24(3):572-6.
[12]. Wang S, Yao R, Tsiftsis TA, Miridakis NI, Qi N. Signal detection in uplink time-varying OFDM systems using RNN with bidirectional LSTM. IEEE Wireless Communications Letters. 2020 Jul 14;9(11):1947-51.
[13]. Akbarpour-Kasgari A, Ardebilipour M. Massive MIMO-OFDM channel estimation via distributed compressed sensing. IEEE Wireless Communications Letters. 2018 Sep 30;8(2):376-9.
[14]. Huang Y, He Y, Luo Q, Shi L, Wu Y. Channel estimation in MIMO–OFDM systems based on a new adaptive greedy algorithm. IEEE Wireless Communications Letters. 2018 Jun 21;8(1):29-32.
[15]. Malik PK, Parthasarthy H. Synthesis of randomness in the radiated fields of antenna array. International Journal of Microwave and Wireless Technologies. 2011 Dec;3(6):701-5.
[16]. He J, Wymeersch H, Juntti M. Channel estimation for RIS-aided mmWave MIMO systems via atomic norm minimization. IEEE Transactions on Wireless Communications. 2021 Apr 7;20(9):5786-97.
[17]. He J, Wymeersch H, Juntti M. Channel estimation for RIS-aided mmWave MIMO systems via atomic norm minimization. IEEE Transactions on Wireless Communications. 2021 Apr 7;20(9):5786-97.
[18]. Mutlu U, Kabalci Y. Channel Estimation In Intelligent Reflecting Surfaces for 5G and Beyond. In2022 4th Global Power, Energy and Communication Conference (GPECOM) 2022 Jun 14 (pp. 586-590). IEEE.
[19]. Vijayalakshmi M, Vijayalakshmi M, Naveena A. A novel intelligent channel estimation strategy for the 5G wireless communication systems. Wireless Personal Communications. 2023 Jun;130(4):2727-51.
[20]. Kaur J, Khan MA. 5G and Beyond: On the Significance of Wireless Channel Estimation. InSoutheastCon 2024 2024 Mar 15 (pp. 28-33). IEEE.

BIOGRAPHIES OF AUTHORS

	Mr. G. Surendher received his M Tech degree in Electronics and communication engineering from JNTU University & Pursuing PhD in Electronics and communication engineering from JNTU University, Hyderabad, India. He is currently working as an Assistant Professor in Dept of ECE, Neil Gogte Institute Technology, Hyderabad. His research interest includes Signal processing, Image Processing, Multiuser & Wireless Communications. He is Member in IEEE and ISTE. He has Published 20+ Scientific Papers in SCI and SCOPUS Journals. He has 19 years of Teaching and Research experience. He can be contacted at email: surendher.g@gmail.com
	Dr. Tipparti Anil Kumar ORCID id: 0009-0007-8350-6427 completed his B.E in Electronics and Communication Engineering from Osmania University, Hyderabad, in the year 1995, M.Tech in Electronics and Communication Engineering from NIT, Kurukshethra, in the year 2002 and has been awarded PhD in Electronics and Communication Engineering from Osmania University, Hyderabad in the year 2009. Dr. T. Anil Kumar has 21 years of Teaching experience and 14 years of Research experience. He can be contacted at email: tvakumar2000@yahoo.co.in.
	Dr. Dhiraj Sunehra ORCID id : 0000-0002-3696-8860 is currently working as a Professor of Electronics and Communication Engineering at JNTUH University College of Engineering, Rajanna Sircilla, Telangana, India. His research interests include Digital and Embedded Systems, Green Wireless Communications and Global Navigation Satellite Systems. He has about 90 research publications in various Journals and Conferences. He has delivered 31 invited lectures and has organized various training programmes and symposia for Faculty and Students in the field of ECE. He is a Senior Member of IEEE, Life Member of IETE, Indian Geophysical Union (IGU), Indian Society for Technical Education (ISTE). He can be contacted at email: dhirajsunehra@yahoo.co.in