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Efficient Channel Prediction Technique Using AMC and Deep Learning Algorithm for 5G (NR) mMTC Devices

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ABSTRACT Efficient utilisation of adaptive modulation and coding ensures the quality transmission of information bits through the significant reduction in bit error rate (BER). Channel prediction using parametric estimation is not efficient for massive machine-type communication (mMTC) devices under the 5G New Radio (NR). In this paper, we have proposed a channel prediction scheme based on a deep learning (DL) algorithm possessed by parametric analysis. In deep learning, the pipeline methodology is used along with the image processing technique to predict the channel condition for optimal selection of the adaptive modulation and coding (AMC) profile. The deep learning-based pipelining approach utilises image restoration (IR) and image super-resolution (SR). The super-resolution method is used to de-noise the low-pixel 2-D image that is obtained from the parametric value of the beacon to predict the channel condition. The estimation results are compared with the conventional minimum mean square error (MMSE) and an approximation to the linear MMSE (ALMMSE) method, which is obtained through channel state information (CSI). The comparison results show that the parametric-enabled deep learning approach is superior, especially in poorer channel conditions. The performance of BER through parametric estimation along with the DL approach is $\sim 66\%$ more efficient as compared to the conventional MMSE method for BPSK mapping.

INDEX TERMS mMTC, 5G (NR), AMC, BER, deep learning, SNR.

I. INTRODUCTION

The vision of fifth-generation (5G) wireless mobile communication is to fulfil QoS (Quality of Services) under robust transmission, end-to-end error-free transmission, with ultra-reliable low-latency communication (URLLC). The optimum utilisation of available spectrum to achieve an efficient transmission rate under the cognitive concept is another key feature of 5G (NR) through the spectral efficient approach. The random fluctuation of noise under the multipath fading channel is an important constraint to achieving spectral efficiency. The joint channel estimation, activity detection and data decoding scheme for massive machine-type communications is explored [1]. Deep learning-based active user detection (AUD) and channel estimation have been investigated in grant-free non-orthogonal multiple access (GF-NOMA) systems. The DL optimised the received NOMA signal and estimated the active devices [2]. Multipath fading channels have a significant impact on wireless broadband in terms of higher bit error rates (BER) and lower throughput. The goal of prior prediction of channel conditions through link adaptation (LA) schemes is to deliver improved spectral efficiency for a quantified target BER by utilising the adaptive modulation and coding scheme based on channel estimation [3].

The multicarrier modulation technique, Orthogonal frequency-division multiplexing (OFDM), is prominently used in communication systems to mitigate the fading effect in wireless channels. The received RF signal is typically distorted due to the random fluctuation of the channel. To retain the original message symbol, appropriate channel encoding is required that must compensate for the errors at the receiver end. An appropriate selection of AMC by the transmitter, generally a pilot carrier, is used to estimate the channel noise. The location and value of the pilot symbol in the carrier signal are known to the transmitter and receiver as well. These pilot symbols could be arranged in a carrier

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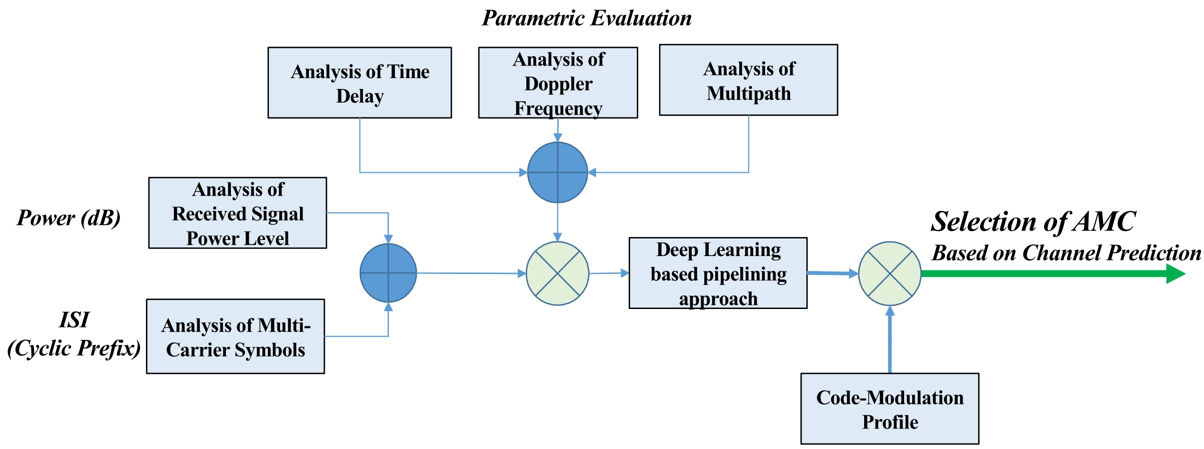

FIGURE 1. Block diagram for parametric estimation.

in different ways, like in a block, comb, or a lattice-type structure [4]. In OFDM subcarriers, these pilot symbols are arranged prior to each subcarrier in a block-type manner, while in the comb type, the pilot is associated with multiple subcarriers instead of each subcarrier with an OFDM symbol. The pilots are mapped under the lattice-type structure, along with the I-Q axis, in a rhombus-shaped constellation. In contrast to [2], [5] proposes active user detection for mMTC devices using centralised prior-based sparse Bayesian learning (cCP-SBL) and decentralised CP-SBL (dCP-SBL) algorithms.

In the conventional least square (LS) and minimum mean square error (MMSE) methods of channel estimation, the pilot carrier to note the channel response is utilized. Our proposed approach to estimating the channel under the deep learning algorithm is highly optimised as the algorithm is applied to the parametric value of the downlink packet. In the least square method, the prediction of statistics about channel information is not covered, while in the minimum mean square error method, it covers the parametric statistics and the noise figure, which produce greater performance as compared to LS. In a fast fading scenario, the actual result of the minimum mean square error method shows poor performance due to correlation and matrix size, so an approximation of the linear version of MMSE is adopted, which reduces the complexity and improves the performance [6].

Deep Learning (DL) has acquired a lot of consideration in the wireless communication system. Deep Learning algorithms are used to improve the performance of existing communication algorithms such as channel encoding algorithms, I-Q mapping [4], sensing information [7], noise mitigation [8], channel state feedback [9], and channel condition prediction [10] for robust communication. In [10], the model of wireless communication is measured as a black-box and applies deep learning architecture, which is utilised for transferring information. The deep learning blocks for communication employ all the essential operations such as encoding, I-Q mapping, and any OFDM subcarrier mapping. The deep learning algorithms are not capable of drawing the channel response in terms of the time-frequency domain, so it is good for those applications where entire responses are required. The channel response is noted as a 2D image array and then applied to a denoising network using a pipeline approach for channel prediction [11]. This work quite differs from [11] as the approach is focused on deep learning over the parametric value, which provides the optimum prediction about the channel. Based on the result, the most significant AMC is triggered.

To perform a parametric calculation of SNR conveyance, there are two conditions which are as follows: (1) estimate the boundaries at the receiver end $f_\gamma(\gamma)$ through an unquantized SNR example, and (2) estimate the boundaries at the transmitter end $f_\gamma(\gamma)$ through channel state indicator. The first approach is utilised when the mobile station (MS) is handled with large amounts of equipped data, while the second approach is appropriate where the MS deals with low processing data, which generally requires a base station (BS) to process the data. In the second approach, the complexity of transferring the data is moved from transmitter to receiver. Then, we continue to introduce a literature overview on the assessment of the boundaries of $f_\gamma(\gamma)$.

In order to evaluate the parametric value, the SNR estimator is to be considered, which is classified as (1) Data-aided (DA) and non-data-aided (NDA). In Data aided based estimation, the receiver is synchronised with the transmitter in prior through a pilot carrier for equalization. In [12], the data-aided estimation of SNR is elaborated under the time domain. The major issue in the data-aided approach to estimating the SNR is the requirement for pilot carriers, which reduces the channel capacity and throughput. A pilot carrier is not required in a non-data-aided approach because it uses the blocks rather than the message-bearing piece for SNR assessment [13]. These assessors are appropriate when unremitting SNR estimation is required. The performance of the non-data aided approach is dependent upon the block length of the message, samples per symbol, and types of I-Q mapping scheme [14]. In [15]–[17], the instantaneous SNR is obtained from the received radio signal through maximum likelihood estimation method (MLE). In all the previously mentioned works, the authors are trying to prompt SNR based evaluation, but no one has applied the DL based approach to the parametric assessment estimation. Figure-1 shows the block diagram of the parametric calculation based on SNR distribution.

In [18], the parametric evaluation of SNR using MLE strategies has been explored. These parametric calculations are further processed by a DL based algorithm for efficient prediction of the channel. The SNR distribution using an unquantised sample of message blocks is performed under the receiver oriented approach. While in transmitter approach channel state, feedback is utilised for SNR distribution to predict the channel. Unlike the traditional prediction approach, where BER is limited to SNR updation, the LA employs the outer loop link adaptation (OLLA) [19], [20]. In Long Term Evolution (LTE), to minimise the BER and enhance the throughput of the system, the AMC and hybrid automatic repeat request (HARQ) employed block error rate (BLER) are analytically examined [21]. The combined effect of AMC and HARQ is explored in the context of P2P communication under the fading channel [22]. The performance of adaptive modulation and coding effects in various fading channels is evaluated for a predefined SNR level [23]. In [24], using the power control parameters, the SNR switching level is explored to obtain the optimum data rate. Be that as it may, the authors have expected the boundaries of SNR dispersion to be known and deduced. In [25], the defective CSI is considered under the Rayleigh fading channel (m = 1, for non-LOS condition) to predict channel. [26] does not tend to m > 1 for the LOS condition. The primary targets of this work are (I) to evaluate parametric using SNR dissemination and (ii) to apply a deep learning enabled pipelining approach to the parametric value to efficient switching of AMC.

A. CONTRIBUTIONS OF THE PAPER

"The parametric estimating technique, combined with deep learning, makes a considerable contribution to predicting the real channel state." The approach's primary highlights are as follows:

- **Step-1:** Hello packet is transmitter over the noisy channel.
- **Step-2:** The impact of noise is being estimated by parameter evaluation such as power, doppler shift, delay, inter symbol interference.
- **Step-3:** The parameter based calculation is share with transmitter through the channel state information (CSI).
- **Step-4:** At the transmitting end, the parametric calculation is further processed by the Deep learning algorithm.
- **Step-5:** Based on deep learning algorithm, an efficient AMC profile is selected.

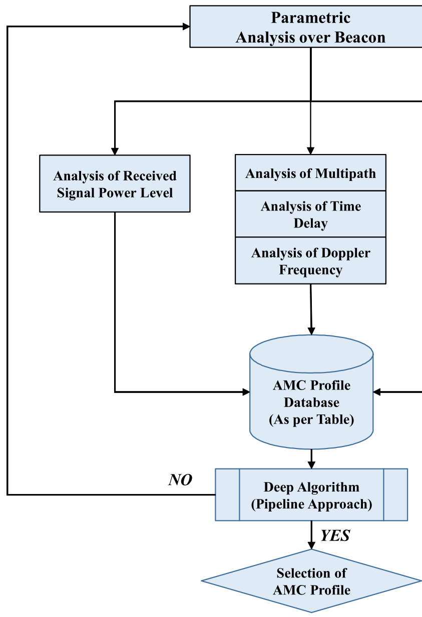

FIGURE 2. Flow chart for proposed methodology.

In our approach the most precise AMC profile is selected as the process of channel prediction is more regress. The result of appropriate selection of AMC is reflected on BER performance. The performance analysis of BER due to deep learning, parametric estimation, conventional AL-MMSE and MMSE is obtained and compared. The results confirm that the DL enabled algorithm is more efficient specially in a poor channel environment.

The paper is organized as follows: The parametric estimation is described in Section-II. Section III discusses the Deep Learning algorithms that use super-resolution and image restoration. The result and discussion are elaborated on Section-IV; conclusions are given in Section-V.

II. PARAMETRIC ESTIMATION

Generally, the packet data unit (PDU) from the data link layer are transmitted over a deafening radio link, and have coherent detection to known receivers. The AMC scheme is capable of effectively responding to these types of channel variations. Figure-3 shows the model scenario of the AMC system based on Frequency Division Duplex (FDD), where the extraction of pilot symbols is utilised to obtain the parametric values. During the transmission process, AMC conducts investigations without varying the bandwidth and transmission power [27]. A Deep Learning based algorithm is utilised for optimum adaption of AMC to lessen the random variation of noise and improve the transmission efficiency.

According to the considerations in Table-1, the analysis and simulation methods are processed accordingly using the AMC code-modulation profile. Two arrangements are used for diversity and the allocation of adjacent

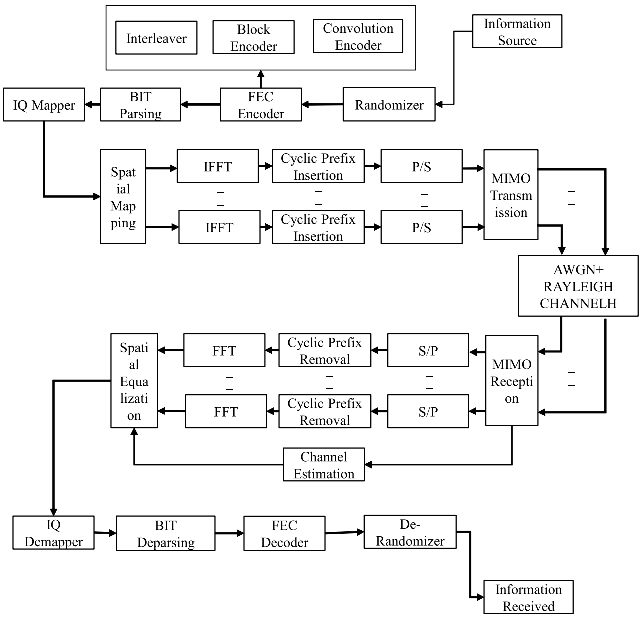

FIGURE 3. Physical layer AMC scenario.

TABLE 1. AMC parameter.

AMC	Modulation M_v	CC code rate	Over-all code rate	SNR threshold dB
Υ^1	BPSK	1/2	1/2	-5
Υ^2	4-QAM	2/3	1/2	-3
Υ^3	16-QAM	2/3	1/2	0
Υ^4	64-QAM	3/4	2/3	3
Υ^5	256-QAM	3/4	2/3	8

subcarriers. The first arrangement uses pseudo-random allocation of sub-carriers to allocate frequency diversity, while the second arrangement uses a sub-channel mechanism to achieve multi-user diversity with the optimum frequency response.

It was observed in [26] that the system throughput is affected by the multipath diversity gain; to mitigate this effect, the AMC is utilized. The joint arrangement of the FEC and modulation system provides a bit-interleaved coded modulation profile.

The optimum selection of AMC through the parametric values utilized the forward error code-modulation combination. The code-modulation profile as per Table-1 could be expressed as:-

$$\Upsilon = \left\{\Upsilon^x : 1 \leq 5\right\} \tag{1}$$

where, x indicates the profile of code-modulation index and AMC code-modulation factor is denoted as Υ as per Table-1. For a given channel condition, Channel state information ζ responsible to feed a current channel noise level to the transmitter. The probability of retrieving the original codeword $d_{cw}x(\eta)$, $d_{cw}(x|\zeta)$ could be obtain by utilizing the AMC profile Υ^x as:-

$$d_{cw}(x \mid \zeta) = \frac{\mathcal{R}(x \mid \zeta) . \mathcal{N}_t[x]}{r[x] . \mathcal{N}_b} \tag{2}$$

where $r[x]$ is code-modulation combination rate, let $\mathcal{N}_b[x]$ symbolize for binary coded symbol and $\mathcal{N}_t[x]$ is the required time for packet transmission $\mathcal{R}(x \mid \zeta)$ is conditional probability of distinct channel state for average throughput. The calculation of $\mathcal{N}_t[x]$ is based on the AMC code modulation profile Υ^x. The values of $\mathcal{N}_b[x]$ are $\mathcal{N}_b$, $\mathcal{N}_b/2$, $\mathcal{N}_b/4$, $\mathcal{N}_b/8$ and $\mathcal{N}_b/16$ for BPSK, 4-QAM, 16-QAM, 64-QAM and 256-QAM respectively. The average carrier to interference noise ratio (CINR) could be attained using the finite length input along present CINR over multiplicity of sole packet under the 5G (NR) OFDM PHY. The ratio of instantaneous signal power to average noise power is described as CINR, $\overline{\varpi}_{CINR}[\mathfrak{k}]$, which is expressed in (3) and (4)

$$\overline{\varpi}_{CINR}[\mathfrak{k}] = \begin{cases} CINR[0], & \mathfrak{k} = 0 \\ \left(1-\alpha_{avg}\right) . \overline{\varpi}_{CINR}[\mathfrak{k}-1] + \alpha_{avg} CINR[\mathfrak{k}], & \mathfrak{k} > 0 \end{cases} \tag{3}$$

$$\overline{\varpi}_{CINR,dB}[\mathfrak{k}] = 10 \log\left(\overline{\varpi}_{CINR}[\mathfrak{k}]\right) \tag{4}$$

where ϱ_{avg} is an averaging factor under the fading channels fed by the receiver and $CINR[\mathfrak{k}]$ is a CINR of $\mathfrak{k}$ packet [2]. AMC profile x would be selected for successive next packet through conditional probability $\hat{\mathbb{I}}(x|\gamma, \Upsilon)$, deliberated with CSI accompanied by ϱ_{avg}. In $\hat{\mathbb{I}}(x \mid \gamma, \Upsilon)$, $\hat{\mathbb{I}}(x|\gamma)$ is probability for a specified channel state under Rayleigh channel model Υ and The conditional probability for that modulation scheme under the AMC profile M_v, is represented by $\mathcal{W}(\mathfrak{v}|\gamma)$

$$\hat{\mathbb{I}}(x|\gamma) = \sum_{x=1}^{5} \hat{\mathbb{I}}(x \mid \gamma, \Upsilon) . \mathcal{W}(\mathfrak{v}|\gamma) . \varrho_{avg} \tag{5}$$

Let ι and γ is the channel parametric for a bit couple, $p(\iota \mid \Upsilon) = q(\Upsilon|\gamma) . \pi(\iota)/\pi(\gamma)$. Conditional probability $\mathcal{W}(\mathfrak{v}|\gamma)$ can be expressed below

$$\mathcal{W}(v|\gamma) = \sum_{\beta \in \Upsilon} p(\iota|\gamma) + \sum_{x \in \Upsilon} p(\mathrm{x}|\gamma) + \sum_{\mathrm{x} \in \Upsilon} p(\mathrm{x} \mid \iota) \tag{6}$$

The channel state indicator ψ, is obtained using the prior channel state information γ feedback through which an appropriate AMC profile will trigged that utilizing modulation index M_v. For each consecutive packet d, a specified AMC profile is adopted for subsequent consecutive packet if $\psi \in \iota_{\vartheta}(x)$.

$$\hat{\mathbb{I}}(x \mid \gamma, \Upsilon) = P\left(\psi \in \iota_{\vartheta}(x) \mid \gamma, \Upsilon\right) \tag{7}$$

In every set of interval $\iota_{\vartheta}(x)$ consist of the parametric of channel state information [28], [29]. Where $\iota_{\vartheta}(x)$ shows the previous packet parametric. Put the values of equation (6) & (7) into (5)

$$\hat{\mathbb{I}}(x|\gamma) = \sum_{n=1}^{8} P(\psi \in \iota_\vartheta(x) \mid \gamma, \Upsilon) . \varrho_{avg} \sum_{\iota\in\gamma} p(\iota|\gamma) + \sum_{x\in\gamma} p(\mathrm{x} \mid \gamma) + \sum_{\mathrm{x}\in\gamma} p(\mathrm{x} \mid \iota) \tag{8}$$

For every $\Upsilon \in \gamma$

$$\sum_{x=1}^{5} \hat{\mathbb{I}}(x|\gamma) = 1 \tag{9}$$

Now for modulation scheme, the BPSK modulation arrangement is to considered. If computational error is ignored, BPSK can be expressed to transmit the single bit as-

$$m(t) = \mathcal{A}\mathrm{b}cos(\omega_c \mathrm{t} + \emptyset) \tag{10}$$

Let $\{+1, -1\}$ is the data set of variable b. T is a symbol duration for t time interval. The phase error calculation $\theta = \emptyset - \overline{\emptyset}$ is analyzed by receiver with phase $\emptyset$. $\overline{\mathcal{A}}$ is the amplitude of modulated carrier and the calculation for modulated carrier $\sigma = \overline{\mathcal{A}}.\mathrm{T}/2$ is obtained on receiver end. Let, $\mu = \Psi$ is a special assumption for ideal channel condition. For a BPSK, parametric could be expressed as-

$$\mathcal{K} = \min\{|\xi + \Psi|, |\xi - \Psi|\} \tag{11}$$

Let $\mathfrak{f}(\chi)$ is a function, which expressed as

$$\mathfrak{f}(\chi) = \min\{|\chi + \Psi|, |\chi - \Psi|\}, \quad -\infty < \chi < \infty \tag{12}$$

T independent uniformly distributed codes are appending with each transmitted message bit in BPSK. In BPSK I-Q mapping, ℓ^{th} symbol is mapped as $\mathcal{Z}^{\text{th}}$ at the receiver constellation point so parametric $\mathcal{K}_\ell = \mathfrak{f}(\mathcal{Z}_\ell)$. Let $\mu_\mathcal{K} = E\{\mathcal{K}_\ell\}$ is the mean, $m_k = E\left\{\mathcal{K}_\ell^2\right\}$ represents the 2^{nd} moment and $\zeta_\mathcal{K}^2 = m_\mathcal{K} - \mu_\mathcal{K}^2$ shows the variance of the I-Q mapping order $\mathcal{K}_\ell(1 \leq l \leq T)$, which consist of identical, independent random variables. From the observed mentioned scenario, this is noticeable that the all the statistic is definite and measurable. The parametric could be modified as-

$$\Gamma_\mathrm{J} = \frac{\varrho}{T\rho} \sum_{\ell=1}^{T} \mathcal{K}_\ell \tag{13}$$

For a given BPSK modulation M_v, constellation arrangements, $M_v = 2_v$ where 'v' is an even number. The value $v = 2; 4; 8$ and 16 for 4-QAM;16-QAM; 64-QAM and 256-QAM respectively, parametric for generalize packet can be expressed as

$$\Gamma_\mathrm{J} = \frac{\varrho}{\mathrm{T}_v\Psi} \sum_{\ell=1}^{T} \mathcal{K}_\ell \tag{14}$$

The channel prediction using (8) over the received packet (14) by considering the Rayleigh fading channel for CINR. Under the swift fluctuating channel, the AMC profile index Υ^1, Υ^2, Υ^3, Υ^4&Υ^5 is adapted accordingly.

A. ALGORITHM (PARAMETRIC EVALUATION)

Algorithm 1 Transmitter Oriented Approach

1. *Analysis of* $\overline{CINR}$, $\overline{BER}$, $\{\gamma_{TH}\}$
   // $\overline{CINR}$ *= Carrier to interference and noise ratio,* $\overline{BER}$ *= Targeted BER*
2. *While BER >* $\overline{BER}$ ***do***
3. *CSI Formation: Generate* ζ
4. *Compute at receiver:* $\mathcal{N}_t[x]$ *and* $\mathcal{N}_b[x]$
   // $\mathcal{N}_t[x]$ *and* $\mathcal{N}_b[x]$ *are the Parametric Distribution*
5. *Obtain:* $\hat{\mathbb{I}}(x \mid \gamma, \Upsilon)$ *and* $\hat{\mathbb{I}}(x|\gamma)$ *to form m' and* $\overline{\gamma}$*'*
6. *Evaluate:* $\hat{\mathbb{I}}(x \mid \gamma, \Upsilon)$ *and* $\hat{\mathbb{I}}(x|\gamma)$
7. *Calculate:* $\mathrm{g}(\chi)$ *using* $\mathcal{K} = \min\{|\xi + \sigma|, |\xi - \sigma|\}$
8. *Code word Adaptation: Using* $d_{cw}(x \mid \zeta) = \frac{\mathcal{R}(x \mid \zeta).\mathcal{N}_t[x]}{r[x].\mathcal{N}_b}$
9. *Feedback to receiver:* $\Gamma_\mathrm{J} = \frac{\varrho}{T\rho} \sum_{\ell=1}^{\mathrm{T}} \mathcal{K}_\ell$
10. *Updation at receiver:* $\Gamma_\mathrm{J} = \frac{\varrho}{\mathrm{T}_v\Psi} \sum_{\ell=1}^{T} \mathcal{K}_\ell$ *using* $\mathcal{K}_\ell = \mathfrak{f}(\mathcal{Z}_\mathcal{L})$
11. *end while*
12. *Execute steps-9 and 10.*

III. DEEP LEARNING ESTIMATION

We are considering deep learning employing a pipelining approach to be applied to noisy image models. An image restoration algorithm is used to mitigate the impact of noise over a 2-D image model. Numerous de-noising algorithms are available considering low resolution. A denoising convolutional neural network (DnCNN) algorithm has explored the normalisation of noise impact using residual learning [30]. The Image Super Resolution (SR) algorithm is used to enhance the performance of the low resolution image. The end-to-end transformation of a low-resolution image to a high-resolution image is explored in a super-resolution convolutional neural network (SRCNN) technique [9].

A. PARAMETRIC VALUATION IMAGE

The physical layer scenario for the mMTC node consists of a MIMO configuration with an OFDM PHY communication link. The channel response in terms of parametric between the T_X and R_X radio links has a complex value that is further explained in terms of a 2-dimensional image as shown in figure-4. The channel response matrix of the H channel is 72×14.

B. NETWORK STRUCTURE

The Deep learning-based pipeline approach is applied to estimate the channel using IR and SR over a noisy 2-dimensional image, called the Channel Network, as shown in figure-4. The predicted rate over the channel at the pilot symbol location h_p^{BP} is measured as the low resolution image shows

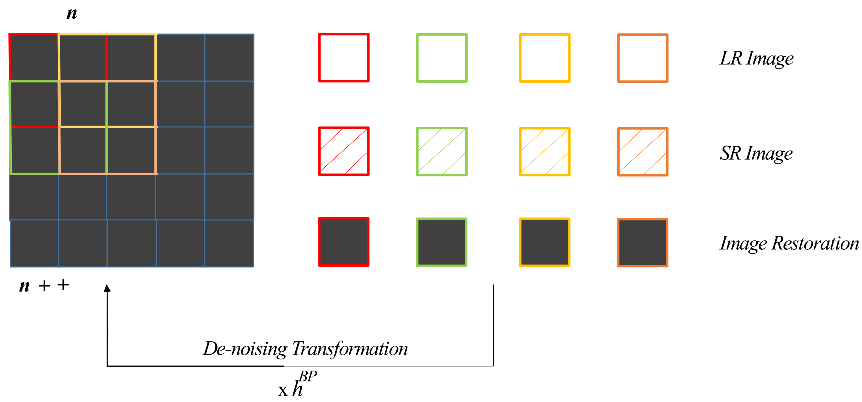

FIGURE 4. Low resolution image to super resolution image.

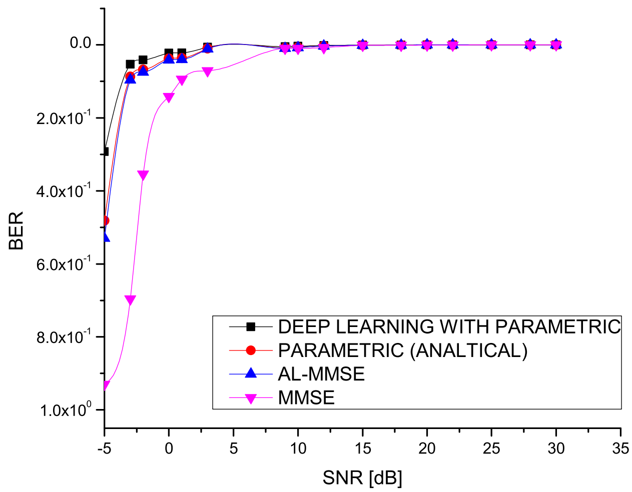

FIGURE 5. Channel estimation performance with code-modulation profile γ^1.

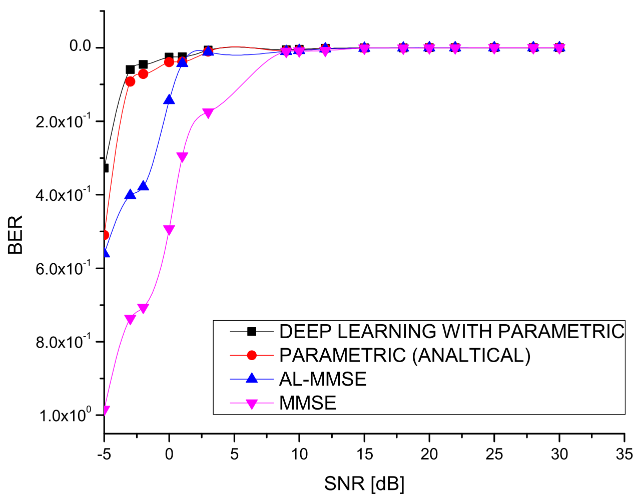

FIGURE 6. Channel estimation performance with code-modulation profile γ^2.

the poor channel state. The de-noising process of the whole channel 2-D image is elaborated in two steps:

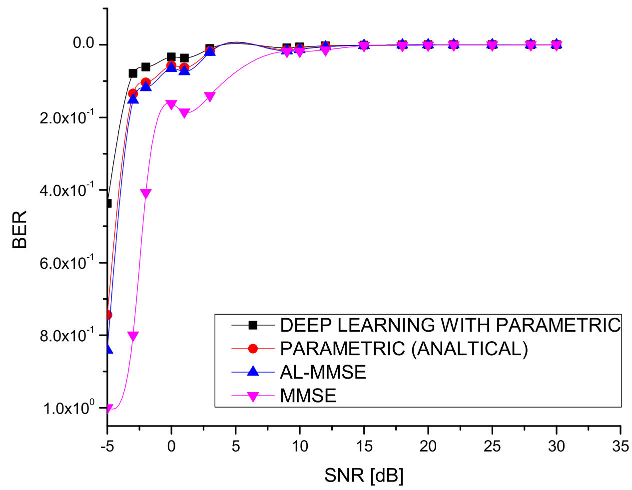

FIGURE 7. Channel estimation performance with code-modulation profile γ^3.

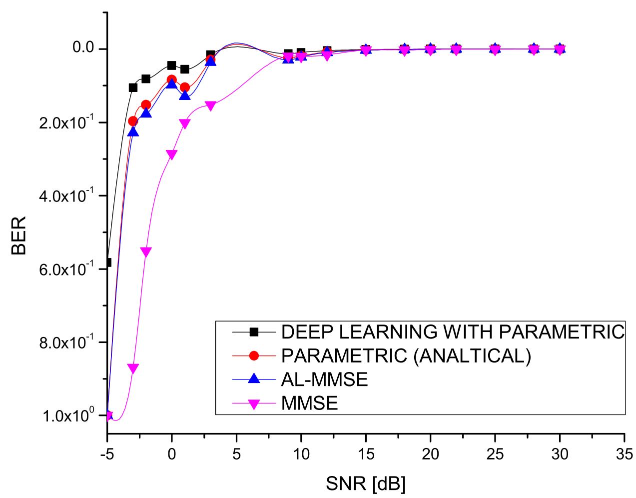

FIGURE 8. Channel estimation performance with code-modulation profile γ^4.

➢ A Super Resolution network is implemented on the pilot carrier location, which takes h_p^{BP} as LR vector and then assesses the unknown channel values of response H.

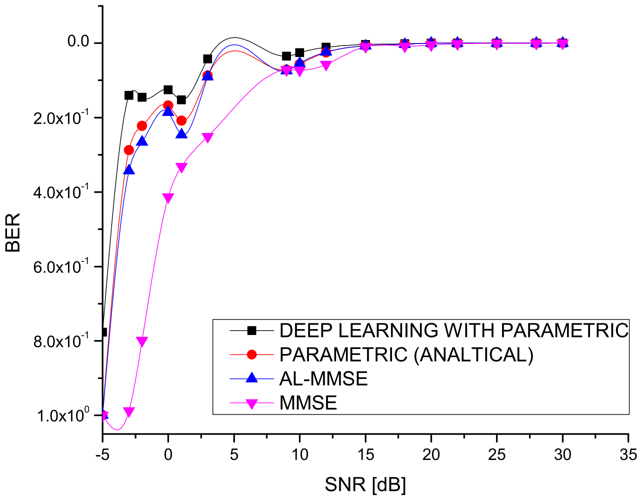

FIGURE 9. **Channel estimation performance with code-modulation profile γ^5.**

➢ The de-noising process is applied using the image restoration method after successfully distinguishing the complex response of the channel in step 1.

Image restoration is utilised as DnCNN [30] while image super resolution is utilised as SRCNN [31]. The SRCNN is a DL-based convolutional neural network algorithm that utilises end-to-end transformation of the LR image into the SR image. As a result, it recovers the image quality of poor resolution or noisy images. The DnCNN uses a DL-based convolution neural network efficient algorithm to normalise a residual image from an LR image. The noiseless image can be estimated by taking the difference between the noisy and residue image. In DnCNN and SRCNN, the image is normalised by the Rectified Linear Unit (ReLU).

IV. SIMULATION RESULT

The overall impact of channel estimation is associated with QoS, which provides the guarantee to the end consumer. To show the robustness of the transmission, the BER results are compared with the widely used baseline algorithms. In the DL-based estimation of channel, the taring rate is fixed at 0.001 and the batch size is 256 under the SR and IR networks. The pilot is tuned with 127 subcarriers with 8 time slots in each frame. To observe the random fluctuation over the channel, the Rayleigh channel model is considered under the fading channel. The delay is observed as ideal.

To observe the performance of channel prediction, the BER of the proposed method is compared with three widely used algorithms, i.e., MMSE [6], AL-MMSE [6], and the parametric based estimation. The 32 pilot symbols are used for synchronisation along with each frame. The performance metric of the proposed method is obtained as the MSE between the predicted and the actual channel. The MMSE method provides superior performance and a lower bound of the attainable MSE under the data-aided channel correlation matrix, which is no longer valid under the random fluctuation channel. The AL-MMSE is a close approximation to the MMSE, which contains all channel statistics. Figure 5-9 shows that for lower SNR values (below 10 dB), the proposed algorithm performed well compared with MMSE, AL-MMSE, and parametric based estimation and has better performance. When the channel is poor, the pipeline algorithm estimates the condition by using a deep low-SNR network.

It can be evidently observed that for SNR inferior to 10 dB, the performance of deep low-SNR is superior compared with another conventional algorithm, though as long as the SNR is superior to 10 dB, the conventional channel estimation method is sufficient.

V. CONCLUSION

The deep learning pipeline algorithm is utilised to estimate the channel condition. The important consideration in this work is that the response of the channel is obtained using the parametric value based on SNR distribution. A 2-dimensional image is obtained based on the channel response of a parametric value under the fading channel model. The Super Resolution and Image Restoration methods are applied to 2-D noisy images to estimate the channel environment. The optimum code modulation profile under the AMC is initiated to mitigate the noise effect on the transmitted bit and, as a result, the most robust transmission is achieved using DL-based estimation compared to the conventional MMSE, AL-MMSE, and the parametric alone. The results show that the DL-based performed well even after the poor channel conditions, i.e., below 10 dB.

REFERENCES

[1] R. B. Di Renna and R. C. de Lamare, "Joint channel estimation, activity detection and data decoding based on dynamic message-scheduling strategies for mMTC," *IEEE Trans. Commun.*, vol. 70, no. 4, pp. 2464–2479, Apr. 2022, doi: 10.1109/TCOMM.2022.3151775.

[2] Y. Ahn, W. Kim, and B. Shim, "Active user detection and channel estimation for massive machine-type communication: Deep learning approach," *IEEE Internet Things J.*, early access, Dec. 3, 2021, doi: 10.1109/JIOT.2021.3132329.

[3] M. Šimko, C. Mehlführer, M. Wrulich, and M. Rupp, "Doubly dispersive channel estimation with scalable complexity," in *Proc. Int. ITG Workshop Smart Antenna (WSA)*, Feb. 2010, pp. 251–256.

[4] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[5] A. Rajoriya, S. Rukhsana, and R. Budhiraja, "Centralized and decentralized active user detection and channel estimation in mMTC," *IEEE Trans. Commun.*, vol. 70, no. 3, pp. 1759–1776, Mar. 2022, doi: 10.1109/TCOMM.2022.3141401.

[6] G. Ku and J. M. Walsh, "Resource allocation and link adaptation in LTE and LTE advanced: A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 3, pp. 1605–1633, 3rd Quart., 2015.

[7] N. Samuel, T. Diskin, and A. Wiesel, "Deep MIMO detection," in *Proc. IEEE 18th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Jul. 2017, pp. 1–5.

[8] D. Erdogmus, D. Rende, J. C. Principe, and T. F. Wong, "Nonlinear channel equalization using multilayer perceptrons with information-theoretic criterion," in *Proc. Neural Netw. Signal Process., IEEE Signal Process. Soc. Workshop*, Sep. 2001, pp. 443–451.

[9] C.-K. Wen, W.-T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 748–751, Oct. 2018.

[10] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[11] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Deep learning-based channel estimation for beamspace mmWave massive MIMO systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 852–855, Oct. 2018.

[12] H. Abeida, "Data-aided SNR estimation in time-variant Rayleigh fading channels," *IEEE Trans. Signal Process.*, vol. 58, no. 11, pp. 5496–5507, Nov. 2010.

[13] M. Hafez, T. Khattab, and H. M. H. Shalaby, "Blind SNR estimation of Gaussian-distributed signals in Nakagami fading channels," *IEEE Trans. Wireless Commun.*, vol. 14, no. 7, pp. 3509–3518, Jul. 2015.

[14] D. R. Pauluzzi and N. C. Beaulieu, "A comparison of SNR estimation techniques for the AWGN channel," *IEEE Trans. Commun.*, vol. 48, no. 10, pp. 1681–1691, Oct. 2000.

[15] Y. Chen and N. C. Beaulieu, "Maximum likelihood estimation of SNR using digitally modulated signals," *IEEE Trans. Wireless Commun.*, vol. 6, no. 1, pp. 210–219, Jan. 2007.

[16] M. A. Raza and A. Hussain, "Maximum likelihood SNR estimation of hyper cubic signals over Gaussian channel," *IEEE Commun. Lett.*, vol. 20, no. 1, pp. 45–48, Jan. 2016.

[17] N. C. Beaulieu and Y. Chen, "Maximum likelihood estimation of local average SNR in Rician fading channels," *IEEE Commun. Lett.*, vol. 9, no. 3, pp. 219–221, Mar. 2005.

[18] S. M. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*. Upper Saddle River, NJ, USA: Prentice-Hall, 1993.

[19] A. Durán, M. Toril, F. Ruiz, and A. Mendo, "Self-optimization algorithm for outer loop link adaptation in LTE," *IEEE Commun. Lett.*, vol. 19, no. 11, pp. 2005–2008, Nov. 2015.

[20] F. Blanquez-Casado, G. Gomez, M. del Carmen Aguayo-Torres, and J. T. Entrambasaguas, "eOLLA: An enhanced outer loop link adaptation for cellular networks," *EURASIP J. Wireless Commun. Netw.*, vol. 2016, no. 1, p. 20, Jan. 2016.

[21] S. Park, R. C. Daniels, and R. W. Heath, Jr., "Optimizing the target error rate for link adaptation," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2015, pp. 1–6.

[22] R. Sassioui, M. Jabi, L. Szczecinski, L. B. Le, M. Benjillali, and B. Pelletier, "HARQ and AMC: Friends or foes?" *IEEE Trans. Commun.*, vol. 65, no. 2, pp. 635–650, Feb. 2017.

[23] M. López-Benítez, "Throughput performance models for adaptive modulation and coding under fading channels," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2016, pp. 1–6.

[24] P. S. Khairnar and N. B. Mehta, "New insights into optimal discrete rate adaptation for average power constrained single and multi-node systems," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 537–543, Feb. 2012.

[25] L. T. Ong, M. Shikh-Bahaei, and J. A. Chambers, "Variable rate and variable power MQAM system based on Bayesian bit error rate and channel estimation techniques," *IEEE Trans. Commun*, vol. 56, no. 2, pp. 177–182, Feb. 2008.

[26] S. S. Borkotoky, S. L. Kottapalli, and M. B. Pursley, "Analytical methods for performance evaluations of adaptive modulation and coding in cognitive radio systems that employ distance statistics," *IEEE Trans. Cognit. Commun. Netw.*, vol. 5, no. 1, pp. 73–81, Mar. 2019, doi: 10.1109/TCCN.2018.2890620.

[27] L. Wan, W. Ma, and Z. Guo, "A cross-layer packet scheduling and subchannel allocation scheme in 802.16e OFDMA system," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Mar. 2007, pp. 1865–1870.

[28] M. B. Pursley and T. C. Royster, IV, "Protocols for adaptation in cognitive radios," in *Cognitive Radio Technology*, B. A. Fette, Ed., 2nd ed. Burlington, MA, USA: Elsevier, 2009, ch. 21, pp. 689–721.

[29] J. S. Harsini, F. Lahouti, M. Levorato, and M. Zorzi, "Analysis of non-cooperative and cooperative type II hybrid ARQ protocols with AMC over correlated fading channels," *IEEE Trans. Wireless Commun.*, vol. 10, no. 3, pp. 877–889, Mar. 2011.

[30] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 38, no. 2, pp. 295–307, Feb. 2016.

[31] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising," *IEEE Trans. Image Process.*, vol. 26, no. 7, pp. 3142–3155, Jul. 2017.

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