High-Order Cumulants and AI-Based Methods for Blind Identification and Equalization in 5G Networks

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***Abstract*—This paper explores and evaluates advanced signal processing techniques for blind channel identification and equalization in modern 5G networks. The focus is on traditional statistical methods and emerging artificial intelligence based on the autoencoder method. The study concentrates on two principal frameworks: high-order cumulants, specifically the fourth-order and sixth-order cumulants, which are capable of exploiting non-Gaussian and higher-order statistical dependencies in digitally modulated signals, and Artificial Intelligence (AI)-based models, particularly autoencoders, which use deep learning architectures to reconstruct or denoise received signals without prior knowledge of the transmission channel. To systematically assess the capabilities of each method, three distinct algorithms were developed and implemented: the fourth-order cumulant, the sixth-order cumulant, and the autoencoder algorithm. These algorithms were applied to 5G signals transmitted over Rayleigh multipath fading channels, modeled using standard propagation profiles such as BRAN-A, BRAN-B, and Proakis B. Simulations were conducted over a wide range of Signal-to-Noise Ratios (SNRs) and varying levels of noise and channel dynamics. Key findings from the simulation results are as follows: The sixth-order cumulant demonstrates superior noise resilience compared to the fourth-order cumulant, making it more suitable for environments with stronger interference or non-Gaussian noise. The autoencoder algorithm achieves the highest estimation and identification accuracy after sufficient training, due to its ability to model complex, nonlinear transformations. However, this comes with increased data requirements and computational cost. The fourth-order cumulant algorithm is computationally efficient, theoretically tractable, and performs well under stationary and low-noise conditions. However, it exhibits a notable performance decline in time-varying or high-noise scenarios. In contrast, the autoencoder algorithm shows enhanced robustness and adaptability to nonlinear, time-varying, and imperfectly modeled environments. Its strength lies in learning the underlying channel effects implicitly from raw data, without requiring a structured analytical model. Nevertheless, this benefit is offset by higher computational complexity and a lack of interpretability compared to the cumulant-based methods. In conclusion, while cumulant-based techniques remain valuable in structured or lightly impaired channels, AI based on autoencoder models, especially autoencoders, offers a more powerful and flexible solution for blind equalization under realistic and challenging 5G conditions.**

***Keywords*—identification, equalization, 5G, High-Order Cumulant (HOS), Bran A, Bran B, Proakis B, Artificial Intelligence (AI), Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), Zero Forcing (ZF), Minimum Mean Square Error (MMSE), Orthogonal Frequency Division Multiple Access (OFDMA)**

I. Introduction

The explosive growth in wireless data demand has driven the evolution of communication systems toward 5G and beyond, necessitating highly efficient, robust, and adaptive signal processing techniques. Modern 5G networks face significant challenges, including severe multipath fading, high mobility, frequency selectivity, and interference among multiple users. One of the critical challenges in this context is the accurate identification and equalization of radio channels, especially in scenarios where the use of pilot symbols is restricted or unavailable-commonly referred to as blind channel estimation and equalization [1]. These blind techniques are essential for improving spectral efficiency, reducing overhead, and ensuring reliable communication in dynamic 5G environments. Traditional blind techniques often rely on second-order statistics, which can be insufficient in rich multipath or non-Gaussian scenarios. In response, High-Order Cumulants (HOCs) [2], particularly the fourth-order and sixth-order, have emerged as powerful tools for blind identification. HOCs capture subtle statistical properties of transmitted signals, enabling the estimation of the channel's impulse response without prior knowledge of transmitted symbols [3, 4]. Their use is especially effective for signals exhibiting non-Gaussian and non-circular characteristics, such as Quadrature Phase Shift Keying (QPSK) or 16-Quadrature Amplitude Modulation (QAM). At the same time, the rapid advancement of Artificial Intelligence (AI) and deep learning [5, 6] has opened new avenues for blind equalization. Models such as autoencoders [7–9] can learn implicit representations of signals and reconstruct transmitted information directly from noisy, distorted observations, without requiring an explicit channel model. AI-based approaches excel in complex, nonlinear, or time-varying environments typical in 5G systems affected by Rayleigh fading, frequency selectivity, and multiuser interference. In this study, we propose a comparative framework that analyzes and contrasts both approaches-high-order cumulants and AI-based autoencoder algorithms for blind identification and equalization in 5G networks. Specifically, we develop three algorithms: a fourth-order cumulant estimator, a sixth-order cumulant estimator, and an autoencoder-based equalizer. Each method is tested over standard 5G multipath channels (e.g., BRAN-A, BRAN-B, and Proakis B) using Orthogonal Frequency Division Multiple Access (OFDMA) waveforms. We design and implement blind estimators of different statistical orders, capturing higher-order signal properties for channel estimation. We develop a deep-learning model trained to reconstruct input signals from distorted received symbols, capturing complex nonlinear channel effects. Furthermore, we evaluate all methods under varying Signal-to-Noise Ratios (SNRs), channel conditions, and signal types, using metrics such as Mean Squared Error

(MSE) and Bit Error Rate (BER). The results demonstrate that while cumulant-based methods are more interpretable and efficient in stationary, low-noise scenarios, AI-based approaches offer superior flexibility and robustness in challenging, dynamic environments. This observation motivates the development of hybrid solutions, which combine statistical features with neural representations, representing a promising direction for next-generation 5G and beyond wireless systems.

II. System model

We are considering baseband OFDMA systems for 5G using modulation schemes, such as QPSK and 16-QAM. The signal experiences multipath fading, which is modeled by the BRAN-A, BRAN-B, and Proakis-B channels, and is also affected by AWGN (Figs. 1 and 2). The received signal is:

$$y(n) = \sum_{i=0}^{p} h(k)x(n-k) + w(n) \tag{1}$$

where:

- $h(k)$: unknown channel coefficients (FIR of order p),
- $x(n)$: transmitted signal,
- $w(n)$: Additive White Gaussian Noise (AWGN),
- $y(n)$: observed output signal.

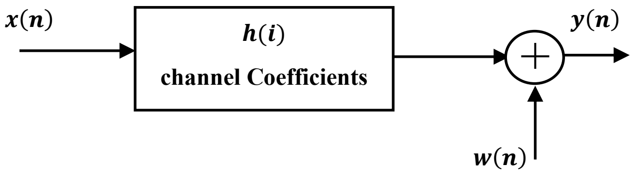


Fig. 1. System model.

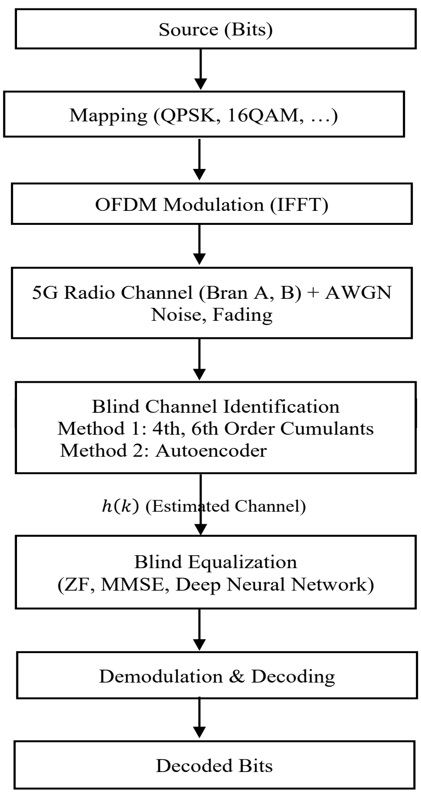


Fig. 2. Functional diagram of blind channel identification and equalization in 5G system.

The reception module performs essential pre-processing of the received OFDM signal. First, synchronization algorithms correct timing, frequency offset, and phase errors caused by the multipath fading channel. Then, the cyclic prefix is removed to restore the original OFDM symbol structure. Finally, a Fast Fourier Transform (FFT) transformation is applied to convert the signal to the frequency domain. This allows each subcarrier to be independently processed. These operations ensure that the input to the blind identification block (cumulants or autoencoder) is properly aligned, making channel estimation and equalization accurate and robust.

III. Blind Algorithms

A. Algorithm Based on 4th Order Cumulant: Alg.4th Order

- Cumulants, which are moments of higher order, capture statistical features of a signal.
- The 4th-order cumulants are invariant to Gaussian noise and sensitive to phase and magnitude distortions.
- By matching the cumulants of the received signal to those of an ideal QPSK signal, the channel can be indirectly estimated.

Let us suppose that:

- The additive noise $n(k)$ is Gaussian, zero mean, possibly colored or symmetric, independent and identically distributed with vanishing moments of order higher than 2.
- The noise $n(t)$ is independent of $x(k)$ and $y(k)$.
- The channel is a causal Finite Impulse Response (FIR) system of known order p with $h(0) = 1$, and $h(i) = 0$ if $i < 0$.
- The m-th order cumulant of the output signal $y(n)$ is related to the input via [10–12]:

$$C_{my}(t_1, \dots, t_{m-1}) = \gamma_{mx} \sum_{-\infty}^{+\infty} h(i)\, h(i+t_1) \dots h(i+t_{m-1}) \tag{2}$$

where γ_{mx} is the m-th order cumulant of the excitation $x(k)$ evaluated at the origin.

Let C_{ny} be the n-th order cumulant of the output, and C_{my} the m-th, then the following relation holds for $n > m$:

$$\sum_{j=0}^{p} h(j) C_{ny(j+t_1,\dots,j+t_{m-1},t_m,\dots,t_{n-1})} = \frac{\gamma_{ne}}{\gamma_{me}} \sum_{i=0}^{p} h(i) \left[\prod_{k=m}^{n-1} h(i+t_k)\right] C_{my}(i+t_1,\dots,i+t_{m-1}) \tag{3}$$

The following gives rise to relationships based on slices:

$$\sum_{j=0}^{p} h(j) \left[\prod_{k=1}^{r} h(j+t_k)\right] C_{ny}(\beta_1,\dots,\beta_r, j+\alpha_1,\dots,\alpha_{n-r-1}) \tag{4}$$

$$= \sum_{i=0}^{p} h(i) \left[\prod_{k=1}^{r} h(i+\beta_k) \right] C_{ny}(t_1, \dots, t_r, i+\alpha_1, \dots, i+\alpha_{n-r-1})$$

For *n* = 3, this simplifies to:

$$\sum_{j=0}^{p} h(j)h(j+t_1)C_{3y}(\beta_1, j+\alpha_1) = \sum_{i=0}^{p} h(i)h(i+\beta_1)C_{3y}(t_1, i+\alpha_1) \quad (5)$$

For *n* = 4, we get:

$$\sum_{i=0}^{p} h(i)h(i+t_1)h(i+t_2)\, C_{4y}(\beta_1, \beta_1, i+\alpha_1) = \sum_{j=0}^{p} h(j)h(j+\beta_1)h(j+\beta_2)C_{4y}(t_1, t_2, +\alpha_1) \quad (6)$$

Let's choose $t_1 = t_2 = p$ and $\beta_1 = \beta_2 = 0$. Then Eq. (6) becomes

$$h(0)h^2(p)C_{4y}(0,0,i+\alpha_1) = \sum_{j=0}^{p} h^3(j)C_{4y}(p,p,j+\alpha_1) \quad (7)$$

Given the FIR structure and causality, we determine that:

$$-p \le \alpha_1 \le p \quad (8)$$

Then, from Eqs. (6) and (7) we obtain the following system of equations:

$$\begin{pmatrix} C_{4y}(p,p,-p) & \cdots & C_{4y}(p,p,0) \\ \vdots & \ddots & \vdots \\ C_{4y}(p,p,0) & \cdots & C_{4y}(p,p,p) \\ \vdots & \ddots & \vdots \\ C_{4y}(p,p,p) & \cdots & C_{4y}(p,p,2p) \end{pmatrix} \begin{pmatrix} h^3(0) \\ \vdots \\ h^3(i) \\ \vdots \\ h^3(p) \end{pmatrix} = h(0)h^2(p) \begin{pmatrix} C_{4y}(0,0,-p) \\ \vdots \\ C_{4y}(0,0,0) \\ \vdots \\ C_{4y}(0,0,p) \end{pmatrix} \quad (9)$$

Since we have assumed that $h(0) = 1$, if we consider that $h(p) \neq 0$ and the cumulant $C_{my}(t_1, \dots, t_{m-1}) = 0$, if one of the variables $t_k > p$, where $k = 1, \dots, m-1$, the system of Eq. (9) will be written as follows:

$$\begin{pmatrix} 0 & \cdots & 0 & C_{4y}(p,p,0) \\ \vdots & \ddots & & \vdots \\ 0 & & & \\ C_{4y}(p,p,0) & \cdots & & C_{4y}(p,p,p) \\ \vdots & & \ddots & 0 \\ & & & \vdots \\ C_{4y}(p,p,p) & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} \frac{1}{h^2(p)} \\ \vdots \\ \frac{h^3(i)}{h^2(p)} \\ \vdots \\ \frac{h^3(p)}{h^2(p)} \end{pmatrix} = \begin{pmatrix} C_{4y}(0,0,-p) \\ \vdots \\ C_{4y}(0,0,0) \\ \vdots \\ C_{4y}(0,0,p) \end{pmatrix} \quad (10)$$

Now, we will formulate the problem in matrix form. Let:

- The left-hand side be a vector d_2 of size $2p+1$,
- The unknowns b_p present the scaled third powers of the channel taps:

$$b_p(i) = \frac{h^3(i)}{h^2(p)}, \quad i = 0, \dots, p \quad (11)$$

- The matrix M is formed by the cumulant:

$$C_{4y}(p, p, j+\alpha_1).$$

Then, the equation becomes:

$$Mb_p = d_2 \quad (12)$$

The least squares solution is:

$$\hat{b}_p = (M^T M)^{-1} M^T d_2 \quad (13)$$

Once we have the estimate of $\hat{b}_p$, we can then estimate the individual taps of the channel coefficients.

For $i = 1, \dots, p-1$:

$$\hat{h}(i) = \text{sign}\left[\hat{b}_p(i)\left(\hat{b}_p(p)\right)^2\right]\left\{abs\left(\hat{b}_p(i)\right)\left(\hat{b}_p(p)\right)^2\right\}^{\frac{1}{3}} \quad (14)$$

where:

$$\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$$

For the last coefficient $h(p)$:

$$\hat{h}(p) = \frac{1}{2} sign\left[\hat{b}_p(p)\right]\left\{abs\left(\hat{b}_p(p)\right) + \left(\frac{1}{\hat{b}_{p(1)}}\right)^{1/2}\right\} \quad (15)$$

Summary of the Algorithm:

- Compute 4th order cumulants $C_{4y}(t_1, t_2, t_3)$ for selected lags,
- Build matrix M and vector d_2 from Eq. (12),
- Solve the linear system via least squares (Eq. (13)),

- Estimate $h(i)$ using Eqs. (14) and (15),
- Normalize so that $h(0) = 1$.

B. Algorithm Based on 6th Order Cumulants: Alg.6th Order

Assumptions

- $x(n)$ is stationary and zero-mean, with normalized cumulants: $cum_2(x) = 1$, $cum_4(x) = \gamma_{4x}$ and $cum_6(x) = \gamma_{6x}$,
- $w(n)$ is a zero mean Gaussian signal uncorrelated with $x(n)$: $cum_m(w) = 0$ for all $m > 2$.

For a stationary, zero mean signal $y(n)$, the general form of the 6th order cumulant is:

$$C_6(\tau_1, \dots, \tau_5) = cum\begin{pmatrix} y(n) \\ y(n+\tau_1), \\ y(n+\tau_2), \\ y(n+\tau_3), \\ y(n+\tau_4), \\ y(n+\tau_5) \end{pmatrix} \tag{16}$$

This expression measures higher-order dependencies among delayed versions of the signal and is zero for Gaussian signals. We select a special structure for the delays to simplify the expressions. For instance ([13]):

$$C_6(p,p,p,k+\alpha_1) = \sum_{j=0}^{p} h^4(j) \cdot h^2(j+p) \cdot \delta_{\alpha_1}(j) \tag{17}$$

where: $\delta_{\alpha_1}(j)$: Kronecker delta that enforces the specific shift pattern.

This choice results algebraic equations involving powers of $h(j)$, which can be linearized or treated as a system of polynomial equations.

Given N samples of the output signal $y(n)$, the 6th order cumulant can be estimated empirically as:

$$\hat{C}_6(\tau_1, \dots, \tau_5) = \frac{1}{N}\sum_{n=1}^{N} y(n),\ y(n+\tau_1), \dots, y(n+\tau_5) \tag{18}$$

Since the additive noise is Gaussian, its contribution to the 6th order cumulant is zero, and the bias terms due to moments can be ignored for large N.

We can gather all cumulant equations into a vector form**:**

$$c_6 = \begin{bmatrix} \hat{C}_6(\tau_{11}, \dots, \tau_{15}) \\ \hat{C}_6(\tau_{21}, \dots, \tau_{25}) \\ \vdots \\ \hat{C}_6(\tau_{p1}, \dots, \tau_{p5}) \end{bmatrix} \tag{19}$$

Each element in c_6 is a nonlinear function of the unknown channel coefficients. We define a corresponding polynomial vector as follows:

$$h_{poly} = \begin{bmatrix} h_0^6 \\ h_0^4 h_1^2 \\ \vdots \\ h_p^6 \end{bmatrix} \tag{20}$$

Now, we will construct the linear system**:**

$$c_6 = M_6 \cdot h_{poly} \tag{21}$$

where:

- $M_6 \in \mathrm{IR}^{M \times K}$ encodes the delay combinations and polynomial coefficients,
- h_{poly} includes monomials of h up to order 6.

We solve the overdetermined system using Least Squares (LS)**:**

$$\hat{h}_{poly} = (M_6^T M_6)^{-1} M_6^T c_6 \tag{22}$$

Next, we invert the monomials to order to retrieve the channel coefficients

$$\hat{h}_j = \sqrt[6]{|\hat{d}_j|} \cdot sign(\hat{d}_j) \tag{23}$$

with:

$$\hat{d}_j = \gamma_{6x} \cdot h_j^6 \tag{24}$$

- $\gamma_{6x} = cum_6(x)$ is 6th order cumulant of signal $x(n)$.
- $\sqrt[6]{|\hat{d}_j|}$: extract the magnitude of the estimated coefficients.
- $sign(\hat{d}_j)$: retains the sign or phase information.

This assumes real-valued cumulants and channels. For complex signals, a phase correction step is needed.

C. Algorithm Based on Autoencoder

1) Principle

Deep learning architectures, such as autoencoders, enable the reconstruction and representation of received signals without prior knowledge of the transmission channel. By learning complex, nonlinear mappings directly from data, they can capture hidden statistical structures, reduce noise and interference, and adapt to time-varying or unknown channels. This makes them very effective for blind equalization in dynamic wireless environments like 5G networks, eliminating the need for pilot symbols or explicit channel models. An autoencoder learns to reconstruct the clean signal from the distorted received signal [14, 15]. It consists of:

- Encoder: Extracts latent representation (*z*),
- Decoder: Reconstructs the signal using (*z*).

2) Architecture

- Input: Time-domain received OFDM blocks,
- Output: Reconstructed block,
- Loss: Reconstruction Mean Squared Error + Kullback-Leibler (KL) divergence.

3) Mathematical formulation

Let:

- $x \in IR^n$: input vector (received signal),
- $z \in IR^k$: latent reresentation with $k < n$,
- $\hat{x} \in IR^n$: reconstructed output.

4) Encoder

Let the input vector be:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in IR^n \quad (25)$$

It may represent, for example, a received OFDMA signal block with n samples.

The encoder performs a linear projection of x into a latent space of dimension k [16]:

$$a = W_e x + b_e \quad (26)$$

where:

- $W_e \in IR^{k\times n}$ is the weight matrix,
- $b_e \in IR^k$ is the encoder bias vector.

This yields an intermediate vector $a \in IR^k$:

$$a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{n} W_{e1j}\, x_j + b_{e1} \\ \sum_{j=1}^{n} W_{e2j}\, x_j + b_{e2} \\ \vdots \\ \sum_{j=1}^{n} W_{ekj}\, x_j + b_{ek} \end{bmatrix} \quad (27)$$

A non-linear activation function is applied element-wise:

$$z_i = \sigma_e(a_i), \quad \text{for } i = 1, \dots, k \quad (28)$$

with:

$$\sigma_e(a_i) = \tanh(a_i) \quad (29)$$

The activation function is used to define the output vector "latent" as follows [17]:

$$z = f_\theta(x) = \sigma_e(a) = \sigma_e(W_e x + b_e) \quad (30)$$

5) Decoder

Reconstructs $\hat{x}$ from z by:

$$\hat{x} = g_\emptyset(z) = \sigma_d(z) = \sigma_d(W_d x + b_d) \quad (31)$$

where:

- $W_d \in IR^{n\times k}$: decoder weight matrix,
- $b_d \in IR^n$: decoder bias vector,
- $\sigma_d(z)$= function activation (sigmoid or linear).

Measures the difference between $\hat{x}$ and x using the loss function Mean Squared Error (MSE):

$$£(x, \hat{x}) = \|x - \hat{x}\|^2 \quad (32)$$

The goal this algorithm is to reconstruct the transmitted signal without explicit knowledge of the channel.

IV. Equalization Algorithms

A. 4th and 6th Order Cumulants Based on ZF and MMSE Equalizations

In blind channel identification for 5G systems, higher order cumulants, specifically the 4th and 6th order, are utilized to extract statistical features from the received signal without the need for pilot sequences. These cumulants effectively capture the non-Gaussian characteristics and structure of the signal, facilitating the estimation of the channel impulse response $\hat{h}$.

After the channel is blindly estimated using cumulant-based methods, conventional linear equalizers like Zero Forcing (ZF) and Minimum Mean Square Error (MMSE) are then applied [18].

1) ZF equalizer

$$\hat{x}_{ZF} = (H^H H)^{-1} H^H y \quad (33)$$

This involves inverting the estimated matrix H, which may amplify noise if H is ill-conditioned.

2) MMSE equalizer

$$\hat{x}_{MMSE} = (H^H H + \sigma I)^{-1} H^H y \quad (34)$$

This enhances robustness against noise by balancing inversion and noise amplification.

Both equalizers rely on the accuracy of the estimated channel $\hat{h}$, which can be obtained using:

- 4th order cumulant**:** suitable for moderately non-Gaussian modulations (e.g., QPSK).
- 6th order cumulant**:** provides enhanced discrimination in the presence of complex nonlinear distortion or higher-order modulation schemes.

This method enables complete blind equalization by combining statistical identification with linear equalization.

3) Autoencoder equalizer

We are looking for a function f, that satisfies the following conditions:

$$\hat{x}(n) = f\big(y(n), y(n-1), \dots, y(n-M+1)\big) \approx x(n) \quad (35)$$

- No explicit knowledge of $h(k)$,
- Learned directly from training pairs (y, x)**.**

An autoencoder is a neural network composed of two parts:

- Encoder : $z = g_\theta\big(y(n), \dots, y(n-M+1)\big)$,
- Decoder: $\hat{x}(n) = d_\emptyset(z)$.

θ and $\emptyset$ are learnable parameters (weights and biases).

The network aims to minimize the error between the output $\hat{x}(n)$ and the true transmitted symbol $x(n)$.

We use the Mean Squared Error (MSE) loss:

$$£_{MSE} = \frac{1}{N}\sum_{n=1}^{N}|\hat{x}(n) - x(n)|^2 \quad (36)$$

Or, separating real and imaginary parts:

$$£_{MSE} = \frac{1}{N}\sum_{n=1}^{N}[\Re\{\hat{x}(n)\} - \Re\{x(n)\}]^2 - [\Im\{\hat{x}(n)\} - \Im\{x(n)\}]^2 \quad (37)$$

We use one-hot encoding for symbols and the cross-entropy loss:

$$£_{CE} = -\sum_{n=1}^{N}\sum_{k=1}^{C} x_k(n)\log\left(\hat{x}(n)\right) \quad (38)$$

where:

- C: number of classes (e.g., $C = 4$ for QPSK),
- $x_k(n)$: 1 if the symbol belongs to class k, else 0,
- $\hat{x}(n)$: predicted probability for class k.

4) Full network forward pass

Input vector:

$$y_n = [\Re\{y(n)\}, \Im\{y(n)\}, \ldots, \Re\{y(n - M + 1)\}, \Im\{y(n - M + 1)\}]^T \in IR^{2M} \quad (39)$$

The network performs:

$$z^{(1)} = \sigma_1(W_1 y_n + b_1)$$

$$z^{(2)} = \sigma_2\left(W_2 z^{(1)} + b_2\right)$$

$$\hat{x}(n) = W_L z^{(L-1)} + b_L \quad (40)$$

- $\hat{x}(n) \in IR^2$ for regression,
- Or $\hat{x}(n) \in [0, 1]^C$ with SoftMax for classification

Weights are updated gradient descent:

$$\theta^{(t+1)} = \theta^{(t)} - \eta\nabla_\theta £ \quad (41)$$

where:

- η: learning rate,
- $\nabla_\theta £$: gradient of loss w.r.t. network weights.

The autoencoder functions as a learned inverse of the unknown channel, replacing traditional equalizers such as:

$$ZF: \hat{x}(n) = \frac{y(n)}{\hat{h}} \text{ or } MSE: \hat{x}(n) = \frac{\hat{h} \times y(n)}{|\hat{h}|^2 + \sigma^2} \quad (42)$$

In the autoencoder, these relationships without are implicitly learned from the data using any linear transformations.

V. Result and Discussion

A. Performance Comparison of 4th and 6th Order Cumulants (Alg. 4th order, Alg. 6th order) and Autoencoder Algorithms:

In this section, we will compare the performance of three algorithms: the 4th Order, 6th Order, and autoencoder algorithms**.** The goal is to assess their accuracy in estimating and identifying the channel impulse responses under various Signal-to-Noise Ratio (SNR) values, using the three multipath channels: BRAN-A**,** BRAN-B, and Proakis B. These channels simulate real-world fading conditions commonly found in wireless communication systems, particularly in the context of 5G technology.

For each channel model, we will calculate the estimated impulse response $\hat{h}$ using the corresponding algorithm, and then compare it to the true impulse response h_{true}.

Tables 1 and 2 compare Mean Squared Error (MSE) values and estimated impulse responses for the Proakis B channel across Signal-to-Noise Ratios (SNRs) from 0 to 30 dB. The autoencoder consistently achieves the lowest and most stable MSE, effectively capturing nonlinear distortions and multipath effects. The fourth-order cumulant method is statistically stable but produces low-accuracy estimates with high MSE and systematic underestimation of channel coefficients. The sixth-order cumulant algorithm offers intermediate performance, reducing MSE relative to the fourth-order method but remaining highly sensitive to noise, resulting in unstable and incomplete channel reconstruction. Overall, AI-based autoencoders demonstrate superior robustness and reliability for blind channel identification in complex 5G environments.

Table 1. Evaluating the MSE variation with respect to SNR

SNR (dB)	MSE (dB) Alg.4th Order	MSE (dB) Alg.6th Order	MSE (dB) Autoencoder Algorithm
0	73.46	−0.2910	−4.7247
5	86.9309	−0.3164	−4.6483
10	80.0924	−2.0485	−5.2946
15	65.8428	−3.1968	−4.4103
20	64.5743	−3.4313	−4.6959
25	54.8433	−3.4913	−4.5835
30	48.1936	−3.4677	−4.8433

Table 2. Estimated Impulse Response for Proakis B

True Channel Coefficients (Proakis B)	Alg.4th Order	Alg.6th Order	Autoencoder Algorithm
0.407	0.357	0.5840	1.0000
0.815	0.735	0.865	0.0312
0.407	0.247	0.4001	0.0136

The simulation results offer a comprehensive evaluation of the proposed blind channel identification and equalization techniques. The autoencoder-based approach demonstrates the most accurate reconstruction of both the magnitude and phase responses of the BRAN-A channel (Fig. 3), thanks to its ability to learn complex nonlinear propagation effects without relying on an explicit analytical model. This method consistently achieves the lowest Mean Squared Error (MSE) across all Signal-to-Noise Ratio (SNR) values (Fig. 3), showcasing robustness to noise and multipath distortions. On the other hand, the 6th-order cumulant-based algorithm (Alg. 6th order), despite its theoretical capacity to exploit higher-order statistical dependencies, shows a significant degradation in performance in practical scenarios. The results indicate instability and large estimation errors in both amplitude and phase (Figs. 4(a), (b)), as well as high MSE values (Fig. 3), suggesting that higher-order cumulants are highly sensitive to noise and unsuitable for BRAN-A channel conditions. The 4th-order cumulant algorithm (Alg. 4th order) provides a more stable and computationally efficient alternative, maintaining low MSE across the tested SNR range (Fig. 3). However, the reconstructed magnitude and phase responses show noticeable deviations from the true channel, especially around deep fades and rapid phase transitions, limiting its accuracy in challenging propagation environments.

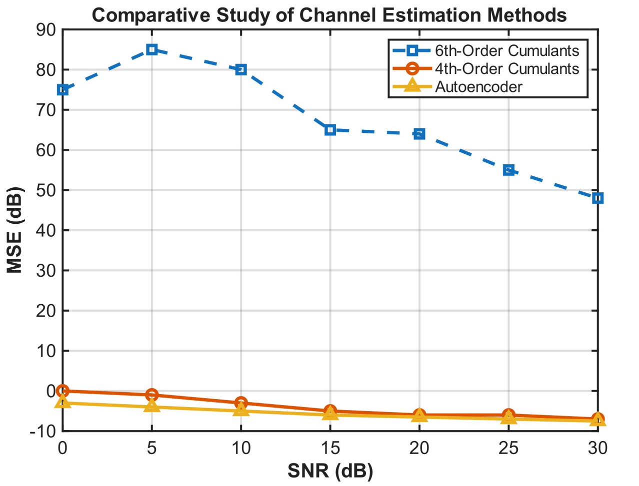
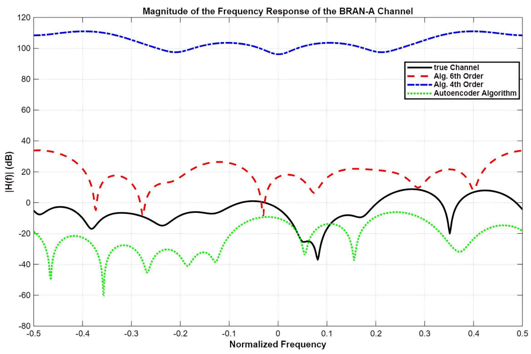
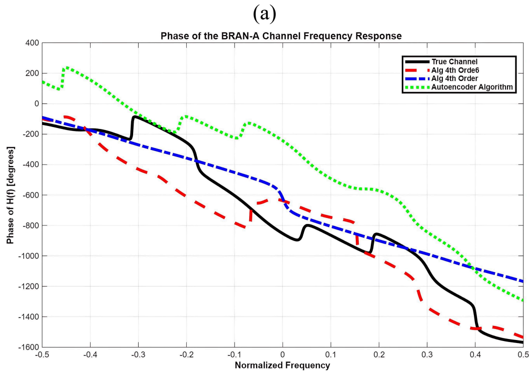


Fig. 3. Compares the MSE as a function of SNR for the 4th Order, 6th order, and autoencoder algorithms.



(a)

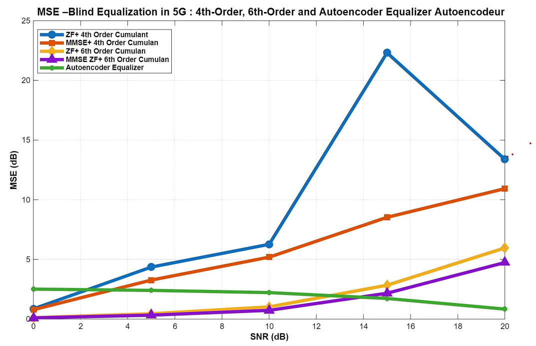


(b)

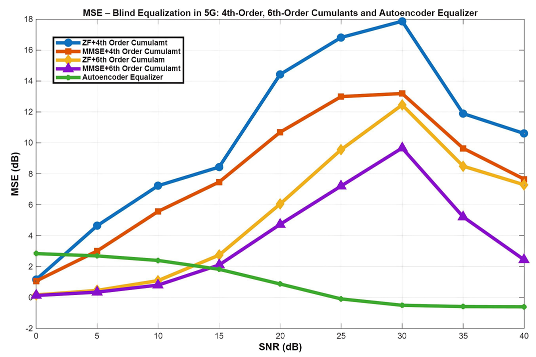
Fig. 4. Compares the magnitude and phase response of the BRAN-A channel identified by the 4th Order, 6th Order, and Autoencoder algorithms. (a) Magnitude response for BRAN-A; (b) Phase response for BRAN-A.

B. *Performance Comparison of 4th Order and 6th Order Algorithms with ZF, MMSE, and Autoencoder Equalizer*

In this section, we will evaluate and compare several blind equalization algorithms applied to 5G communication systems operating over a multipath fading channel modeled by the ETSI BRAN-B standard. The equalizers under study include an algorithm based on fourth-order cumulants, an algorithm based on sixth-order cumulants, classical equalization methods such as Zero-Forcing (ZF) and Minimum Mean Square Error (MMSE) applied to the cumulant-based channel estimates, and a neural network-based autoencoder equalizer trained to perform blind equalization. The objective is to analyze the effectiveness of these algorithms in mitigating channel impairments and noise, thereby enhancing signal recovery performance.

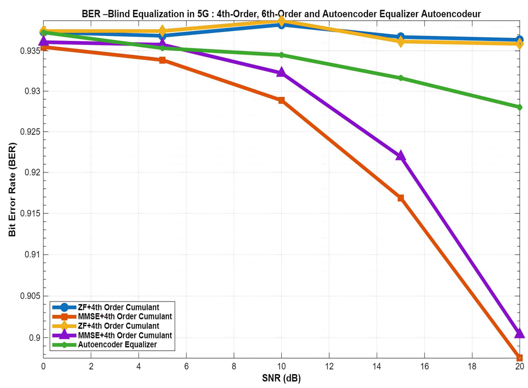


(a)

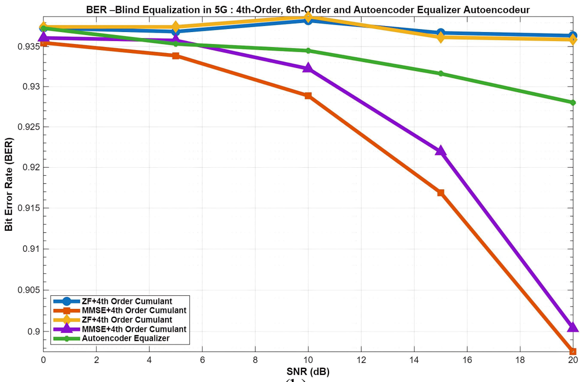


(b)

Fig. 5. Compares the MSE in blind equalization of a 5G system using 4th Order and 6th Order cumulants with ZF, MMSE methods, and the autoencoder equalizer. (a) Calculate the MSE with SNR ranging from 0 to 20 dB; (b) Calculate the MSE with SNR ranging from 0 to 40 dB.



(a)



(b)

Fig. 6. Compares the Bit Error Rate (BER) of a 5G system using 4th Order and 6th Order cumulants with ZF, MMSE methods, and the autoencoder equalizer. (a) Calculate the BER with SNR ranging from 0 to 20 dB; (b) Calculate the BER with SNR ranging from 0 to 40 dB.

This study compares blind channel equalization methods in 5G systems using fourth-order and sixth-order cumulants, as well as autoencoder-based approaches. Sixth-order cumulants provide more accurate channel estimation than fourth-order cumulants, especially at low SNRs, due to better exploitation of higher-order signal statistics. MMSE equalizers outperform ZF equalizers by accounting for noise, resulting in reduced error rates (Fig. 5(a) and (b)). Autoencoder equalizers demonstrate robustness and adaptability, often surpassing classical methods at moderate to high SNRs by learning nonlinear channel effects and noise characteristics (Fig. 5(a) and (b)). At very high SNRs, all methods converge to low MSE and BER, while at low SNR, the sixth-order cumulant and autoencoder retain clear advantages (Fig. 6(a) and (b)). Regarding algorithmic complexity and performance, the fourth-order cumulant method exhibits low complexity with average MSE and BER performance and limited robustness to noise. The sixth-order cumulant method involves moderate complexity with good MSE and BER performance and improved robustness. The autoencoder equalizer has higher computational complexity but achieves excellent MSE and BER performance with very strong robustness to noise. The emphasis on sixth-order cumulants is justified by their ability to provide richer statistical information, greater robustness at low SNR, and improved identifiability of complex channels compared to fourth-order cumulants. While C4 remains simpler and widely used, C6 enables more accurate and reliable blind channel estimation, particularly for advanced 5G/6G, THz, multiuser, and high-order modulation systems. Overall, cumulant-based methods are efficient and interpretable in low-noise, stationary environments, whereas AI-based methods offer superior flexibility and robustness in dynamic and noisy channels, motivating the development of hybrid approaches.

Table 3. The qualitative summary highlights the strengths

Equalization Method	Algorithmic complexity	MSE performance	BER performance	Noise
4th-Order Cumulant	Low	Average	Average	Low
6th-Order Cumulant	Average	Good	Good	Average
Autoencoder Equalizer	High	Excellent	Excellent	Very Robust

As shown in Table 3, the proposed approaches demonstrate distinct performance behaviors, with the hybrid method achieving improved accuracy compared to the standalone cumulant-based and autoencoder-based techniques.

VI. Limitations and Future Work

This study is primarily validated through simulations under controlled channel conditions. Real-world impairments such as hardware nonlinearities, synchronization errors, and phase noise were not fully considered. The computational complexity of sixth-order cumulants and autoencoder-based models may limit scalability and real-time implementation, especially in massive MIMO and multiuser scenarios. Additionally, the generalization capability of AI-based equalizers in highly dynamic and fast time-varying channels remains partially unexplored.

Future work should focus on adaptive hybrid frameworks that combine cumulants and AI depending on channel conditions. Lightweight and online learning models should be developed to reduce complexity, and extensions to mmWave, THz, and 6G systems should be explored. Advanced tensor decomposition methods and explainable AI techniques are also promising directions for further research. Finally, experimental validation on real 5G testbeds is essential to confirm practical feasibility.

VII. Conclusion

This study evaluates blind channel identification and equalization techniques for 5G wireless systems, focusing on high-order statistical methods and AI-driven approaches. Fourth- and sixth-order cumulant algorithms extract non-Gaussian features from received signals without pilot symbols. While fourth-order cumulants perform well under standard noise conditions, their accuracy decreases at low SNRs. Sixth-order cumulants enhance robustness by capturing more complex statistical dependencies, achieving lower Mean Square Error (MSE) than fourth-order methods in noisy environments. Zero-Forcing (ZF) equalizers are sensitive to noise, whereas Minimum Mean Square Error (MMSE) equalizers outperform ZF by explicitly considering noise effects. Constellation diagrams and spectral analysis show that cumulant-based methods mitigate inter-symbol interference, while AI-based autoencoders provide superior performance by modeling nonlinear and time-varying channel effects directly from received data. Latent space visualizations confirm effective feature separation, and hybrid models combining cumulants with autoencoders leverage structured statistical inputs for improved estimation accuracy, reduced computational cost, and robust performance across SNR levels. However, higher-order cumulants are highly sensitive to noise, and AI-based models require significant training data and computational resources. Future research should explore adaptive hybrid frameworks for real-time deployment, integrate reinforcement learning for dynamic channel tracking, and evaluate performance in diverse 5G/6G scenarios, including massive MIMO and THz communications, to further enhance robustness, scalability, and practical applicability in complex multipath environments.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S. Elkassimi conducted the research, formulated the blind algorithms, and performed the experimental tests. S. Safi and B. Manaut reviewed the manuscript. All authors contributed to the discussion of results and approved the final version of the manuscript.

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