

Original Article

Channel-Aware Hybrid Precoding and Gaussianized Companding for Energy-Efficient PAPR Reduction in Next-Generation Multicarrier Waveforms

Ponmani Raja M¹, Sujatha S², Prajoon P³

^{1,2}Department of Electronics & Communication Engineering, Christ (Deemed to be University), Bangalore, India

³Department of Electronics & Communication Engineering, Jyothi Engineering College, Kerala, India.

¹Corresponding Author : ponmani.raja@res.christuniversity.in

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Abstract - Peak-to-Average Power Ratio (PAPR) remains a major limitation in multicarrier communication because large waveform peaks reduce power-amplifier efficiency and may degrade reliability and spectral containment while increasing energy consumption. This paper presents a Channel-Aware Hybrid Precoding and Gaussianized Companding (CA-HPGC) framework for energy-efficient PAPR reduction in OFDM, UPMC, and OTFS waveforms. The framework observes channel-state information, Signal-to-Noise Ratio, Doppler condition, modulation order, power-amplifier headroom, and quality-of-service requirements to select SRC, DCT, DHT, or hybrid precoding. It then applies selective Gaussianized companding only to statistically dominant envelope samples. A multi-objective controller jointly considers PAPR, bit-error rate, error vector magnitude, out-of-band emission, energy per bit, and latency. In the simulation-based evaluation, CA-HPGC reduces PAPR to 6.50 dB for UPMC and 6.10 dB for OTFS at CCDF of 10^{-3} . At 20 dB SNR, the proposed OTFS achieves BER of 2.8×10^{-4} , EVM of 2.40%, and OOB power of -45.10 dBm. Energy efficiency reaches 2.17 Mbit/J with 0.46 μ J/bit. These findings indicate that adaptive signal shaping can reduce peaks while preserving reliability and transmitter energy efficiency.

Keywords - Channel-Aware precoding, Gaussianized companding, Peak-to-Average Power Ratio, UPMC, OTFS, Energy-Efficient communications, Multicarrier waveforms.

1. Introduction

Under time-varying propagation conditions, future wireless systems must enable high data speeds, reliable connectivity, energy-aware operation, and different service requirements. Multicarrier waveforms offer variable spectrum allocation and strong equalisation in frequency-selective channels, making them essential to this goal. Orthogonal Frequency Division Multiplexing (OFDM) is widely deployed, while Universal Filtered Multicarrier (UPMC) improves subband spectral containment, and Orthogonal Time-Frequency Space (OTFS) provides resilience in high-mobility delay-Doppler channels. However, all these waveforms can exhibit large envelope fluctuations when independently modulated subcarriers or symbols add constructively. The resulting Peak-to-Average Power Ratio (PAPR) forces the power amplifier to operate with substantial back-off, thereby reducing power efficiency and potentially increasing nonlinear distortion. Recent research has investigated learning-assisted, transform-based, and constrained optimisation approaches for PAPR reduction. Abdullah et al. [1] introduced an asymmetrical autoencoder approach for CP-OFDM and demonstrated the potential of

deep learning to reshape waveform amplitudes. Da Silva et al. [2] reviewed machine-learning-based PAPR techniques and highlighted the importance of jointly considering complexity, side information, and signal quality. Pfletschinger et al. [3] further showed that nonlinear PAPR-reduction schemes should be assessed beyond PAPR alone, since mutual information and distortion effects are closely related. These studies establish the value of intelligent signal processing, but most available methods remain waveform-specific or do not explicitly adapt their parameters to instantaneous channel and power-amplifier conditions. Channel-informed precoding has gained increasing attention in multi-antenna systems. Kakehashi et al. [4] used null-space-based processing for PAPR reduction in relay-assisted MIMO-OFDM, while Saito et al. [5] developed parallel null-constrained peak-cancellation methods for massive MIMO-OFDM. Bolla and Singh [6] formulated joint QoS and PAPR reduction for energy-efficient massive-MIMO transmission. Qin et al. [7] proposed symbol-level precoding that uses channel-state information and constructive interference to control PAPR in multi-user MISO-OFDM. Although these contributions improve transmitter-side control, they are mainly designed for MIMO-



OFDM architectures and do not integrate adaptive companding with a unified multiwaveform framework.

For high-mobility systems, OTFS-specific PAPR reduction has also progressed. An automatic amplitude-reduction neural technique for OTFS by Kumar et al. [8] shows the benefits of data-driven peak control. Farid et al. [9] found that carefully selected transforms can reduce PAPR without harmful BER penalties in transform-based precoding for power-efficient optical OFDM. Recently, Ramesh et al. [10] used graph-based channel-state encoding and reinforcement learning to minimise PAPR in multi-user MIMO systems. Dynamically selecting hybrid precoding, selective peak processing, and distribution-aware companding parameters based on channel state, waveform type, energy demand, and modulation order is still a research gap. The present study is developed as a methodological extension beyond an earlier UPMC-focused adaptive orthogonal precoding and Gaussianized companding framework. The earlier framework employed transform adaptation primarily according to signal-to-noise ratio and modulation characteristics, followed by Gaussianized companding for peak-envelope control in a UPMC transmission setting.

In contrast, the proposed Channel-Aware Hybrid Precoding and Gaussianized Companding (CA-HPGC) model introduces a state-conditioned decision mechanism that jointly considers channel state information, Doppler condition, waveform type, power-amplifier headroom, quality-of-service requirement, and modulation order. It further employs a configurable transform bank and state-dependent hybrid precoder weighting rather than relying only on transform selection. The companding stage is reformulated to adapt its threshold, compression strength, and Gaussian-tail boundary according to the current channel state, while selective processing is explicitly separated into frequency-domain precoder configuration and time-domain dominant-envelope sample treatment. These differences are evaluated through a matched comparison and component-wise ablation analysis under identical UPMC simulation conditions.

This paper continues as follows. Section 2 reviews relevant literature and finds research gaps. Section 3 describes the CA-HPGC system model, hybrid precoding, Gaussianized companding, and optimisation formulation. Simulation configuration and evaluation metrics are in Section 4. Comparative results, robustness, ablation analysis, and energy-efficiency trade-off are covered in Section 5. Section 6 closes the paper and suggests future research.

2. Literature Review

Wei et al. [11] examined the UPMC waveform under various channel conditions and system configurations. The investigation demonstrated that UPMC has greater spectrum localisation than OFDM and evaluated its BER, PAPR, carrier-frequency offset, and timing-offset behaviour. The

study primarily evaluated waveform performance and did not introduce an adaptive PAPR-reduction method. Channel information was not used to dynamically select precoding or companding settings. In an IEEE Access publication, Almutairi, Al-Gharabally, and Krishna [12] examined hybrid PAPR-reduction methods for 5G UPMC systems. Combining methods reduced peaks better than clipping, companding, or related procedures alone. PAPR, energy efficiency, EVM, spectrum containment, and latency were not optimised together since the method used preset design settings. It also lacked channel-aware adaptability for time-varying wireless conditions. Al-Rayif et al. [13] studied PAPR reduction in UPMC for 5G wireless communication using traditional peak-control algorithms in an IEEE Access publication. The study showed that UPMC PAPR can be reduced; however, peak suppression involves a trade-off with BER degradation. Most of its processing parameters are waveform-specific. It lacks an intelligent system for picking a technique based on instantaneous channel quality or energy demand.

For UPMC, Taşpınar and Şimşir [14] created a migrating-birds-optimization-based mapping approach using cyclic bit flipping. The algorithm flips the searched candidate phase sequences better than standard SLM, reducing PAPR. However, optimisation focused on the PAPR objective and candidate generation, increasing computational cost. BER, EVM, OOB emission, energy efficiency, and channel-dependent parameter adaptation were not addressed together.

Mounir et al. [15] suggested a hybrid precoding-companding paradigm for 5G-and-beyond multicarrier PAPR reduction. They found that transform-domain precoding and nonlinear companding reduce PAPR better together. However, real-time channel conditions and service requirements did not influence transformation and companding settings. Thus, the architecture allows energy-, channel-, and multi-objective control. Chintala and Sundru [16] studied quantised precoding and companding for PAPR reduction in UPMC-based massive-MIMO downlink transmission.

The work improves power efficiency with constant-envelope-oriented precoding and nonlinear companding for finite-resolution signal processing. It prioritised massive-MIMO UPMC above a next-generation multicarrier framework. It also did not provide a channel-aware hybrid controller that balances PAPR, BER, EVM, OOB emission, energy per bit, and latency. In a Transactions on Emerging Telecommunications Technologies article, Bitra et al. [17] suggested rooting-based companding transforms to lower PAPR in OTFS signals. The study analysed logarithmic rooting, rooting, and rooting-based μ -law companding, identifying parameter ranges affecting PAPR and BER. Although beneficial for high-mobility OTFS transmission, the approach uses preset transform parameters. Not included are adaptive precoding, energy-aware optimisation, and channel-responsive companding management.

Kumar et al. [18] studied OTFS modulation hybrid PAPR algorithms. The study found that complementary PAPR-reduction techniques improve peak reduction while retaining BER and spectral features. However, the method was created for OTFS and did not provide an adaptive framework for UPMC, OFDM, and OTFS. Energy efficiency is not explicitly modelled as a primary optimisation target. In a Wireless Personal Communications publication, Gopal, Reddy, and Chintagunta [19] reduced OTFS PAPR using symbol interferometry and μ -law or A-law companding. Their simulation and power-amplifier assessment indicated that spreading symbols before companding reduces high envelope peaks with acceptable signal-quality consequences.

Fixed companding may not be ideal across SNRs, Doppler circumstances, modulation orders, and amplifier operating regions. A channel-aware companding technique with adaptive parameter selection is suggested by the study. Kumar et al. [20] introduced a low-complexity hybrid approach to enhance PAPR, BER, and power spectral density in OTFS across various channel conditions in an ETRI Journal article. The study showed hybrid signal processing improves several communication metrics. It does not explicitly set energy efficiency and latency goals or employ an intelligent controller to pick hybrid characteristics online. Its OTFS-centered design allows for a broader next-generation multicarrier solution.

2.1.1. Research Gaps

1. Most existing methods use fixed precoding, companding, or optimisation parameters; they do not adapt the signal-shaping process to instantaneous CSI, SNR, Doppler spread, modulation order, or amplifier condition.
2. Current UPMC studies generally optimise PAPR alone, or at most PAPR and BER. Joint optimisation of PAPR, BER, EVM, OOB emission, energy per bit, and latency remains limited.
3. Hybrid precoding-companding methods exist, but Gaussianized companding integrated with channel-aware hybrid precoding has not been sufficiently investigated.
4. Many methods are designed for only one waveform, such as UPMC or OTFS. A unified, scalable approach for next-generation multicarrier waveforms is still needed.
5. Energy efficiency is often assumed as an indirect advantage of PAPR reduction rather than being measured and optimised directly.

Therefore, the proposed work develops a Channel-Aware Hybrid Precoding and Gaussianized Companding framework that dynamically selects signal-shaping parameters and jointly minimises PAPR while preserving reliability, spectral quality, and energy efficiency.

3. Proposed Model

Table 1. Methodological distinction between the earlier AHO-PCG framework and CA-HPGC

Aspect	Earlier AHO-PCG framework	Present CA-HPGC framework	Distinction and inheritance status
Primary transmission scope	Designed exclusively for UPMC transmission with 3GPP LTE-oriented UPMC settings.	Formulated for OFDM, UPMC, and OTFS, with waveform-dependent modulation operations.	New scope, but not independently sufficient novelty. The methodological distinction must be validated under matched UPMC conditions.
Signal-adaptation inputs	Uses real-time SNR, modulation and coding scheme, instantaneous energy characteristics, empirical amplitude statistics, subband activity, and signal loading.	Uses a channel-state vector comprising estimated SNR, Doppler frequency, channel-quality indicator, modulation order, waveform type, PA headroom, and QoS requirement.	Extended controller state. CA-HPGC adds Doppler, explicit channel-quality information, waveform identity, PA headroom, and QoS.
Transform bank	Selects one transform from DFT, SRC, and Zadoff-Chu Transform (ZCT).	Uses SRC, DCT, DHT, or a hybrid configuration.	Modified transform bank. DFT and ZCT are replaced by DCT and DHT; SRC is retained.
Precoding formulation	Applies a selected transform to each UPMC subband, $x_m' = P_{m,u}x_m$, where $P_{m,u}$ is selected from the DFT, SRC, or ZCT bank.	Forms a hybrid matrix, $P_u = \alpha_1 P_{\text{SRC}} + \alpha_2 P_{\text{DCT}} + \alpha_3 P_{\text{DHT}}$, subject to non-negative coefficients summing to one.	New mathematical formulation. AHO-PCG performs discrete single-transform selection, whereas CA-HPGC introduces coefficient-based hybrid mixing.
Precoder-selection rule	Uses a lightweight meta-controller that chooses the transform with the highest conditional selection	Selects from SRC, DCT, DHT, and hybrid modes using a score based on predicted PAPR reduction, energy-efficiency gain,	Extended decision criterion. The CA-HPGC score adds energy-efficiency and complexity terms and conditions selection on the

	probability given SNR and modulation/coding scheme.	BER, EVM, and computational cost.	broader channel-state vector.
Gaussianization principle	Uses the empirical CDF of the signal amplitude and inverse Gaussian CDF mapping to obtain a Gaussian-like amplitude variable.	Uses the empirical CDF of time-domain waveform magnitudes and inverse Gaussian CDF mapping to obtain a Gaussian reference quantile.	Inherited foundation. Both frameworks use empirical-CDF-based Gaussianization; this common mechanism must be disclosed rather than claimed as entirely new.
Companing law	Applies logarithmic Gaussianized dynamic companing, $\mathcal{C}(G[n]) = \text{sign}(G[n]) \log(1 + \alpha G[n])$, with a variance-related factor $\alpha = \lambda/\sigma_A$.	Applies Gaussian-tail-controlled exponential attenuation, $g_1[n] - \exp(-\mu_t \max\{0, g_1[n] - \theta_t\})$, governed by strength μ_t and tail boundary θ_t .	New companing function. CA-HPGC replaces the earlier logarithmic, variance-based law with a tail-activated exponential gain law.
Selective-processing domain	Selective Subcarrier Companing identifies high-power frequency-domain subcarriers using, $K_{\text{comp}} = \{k: P_k > \mu_P + \beta \sigma_P\}$ Only selected subcarriers undergo companing before IFFT reconstruction.	Selective dominant-sample processing identifies high-magnitude time-domain samples using, $D_t = \{n: x[n] > \mu_{x,t} + k_t \sigma_{x,t}\}$ Ordinary samples are preserved.	Fundamental procedural difference. AHO-PCG selects frequency-domain subcarriers, whereas CA-HPGC selectively modifies time-domain envelope samples after waveform generation.
Processing sequence	UFMC subband mapping and selected orthogonal precoding are followed by Gaussianized dynamic companing and selective subcarrier processing.	Channel-state estimation is followed by hybrid precoding, waveform-specific modulation, dominant time-domain sample identification, Gaussianized tail companing, and power normalization.	Reordered and extended the procedure. CA-HPGC separates frequency-domain precoding from time-domain nonlinear sample shaping.
Optimization objective	Jointly balances BER, EVM, and OOB emission through frame-level feedback and rule-based or gradient-free parameter updates.	Defines a normalized joint objective over PAPR, BER, EVM, OOB power, energy per bit, and processing latency.	Extended objective. Energy per bit and latency are added explicitly; however, the manuscript must state the one optimizer actually implemented and its parameter settings.
Energy model	Discusses energy-aware transform selection and execution-time implications, but does not provide an explicit PA-efficiency and energy-per-bit formulation.	Models PA efficiency as a function of PAPR and PA headroom, and derives energy per bit and energy efficiency from PA, baseband, RF, and delivered-rate terms.	New energy-accounting formulation. This claim requires reproducible PA-model parameters and matched AHO-PCG comparison results.
Evaluation design	Evaluated using UFMC, AWGN, a 1024-point FFT, QPSK/16-PSK/64-QAM, and Python-based simulation.	Reports OFDM, UFMC, and OTFS simulations across AWGN, Rayleigh, Rician, vehicular, and high-mobility channels, with Doppler variation and multiple QAM orders.	Broader evaluation setting. A direct AHO-PCG-versus-CA-HPGC comparison must still use the same UFMC configuration, channel model, modulation, FFT size, frame count, and performance calculations.

Figure 1 presents the complete workflow of the proposed CA-HPGC architecture. The process begins with input data mapping and waveform selection, where OFDM, UFMC, or OTFS is configured with an appropriate QAM order. SNR, Doppler, channel-state information, power-amplifier headroom, and QoS are then estimated. The channel-aware

controller chooses the hybrid precoder, dominant-sample threshold, and Gaussianized companing parameters from these parameters. To distribute symbol energy and reduce envelope peaks, SRC, DCT, DHT, or their hybrid combination is utilised. Only statistically dominant samples are compressed via selective Gaussianized companing,

preserving ordinary samples to limit increases in EVM and BER. The processed waveform is broadcast across the wireless channel and recovered via equalisation, inverse precoding, and detection after power normalisation. Finally,

the performance monitor evaluates PAPR, BER, EVM, OOB emission, energy efficiency, and latency, and feeds these measures back to refine subsequent channel-aware decisions.

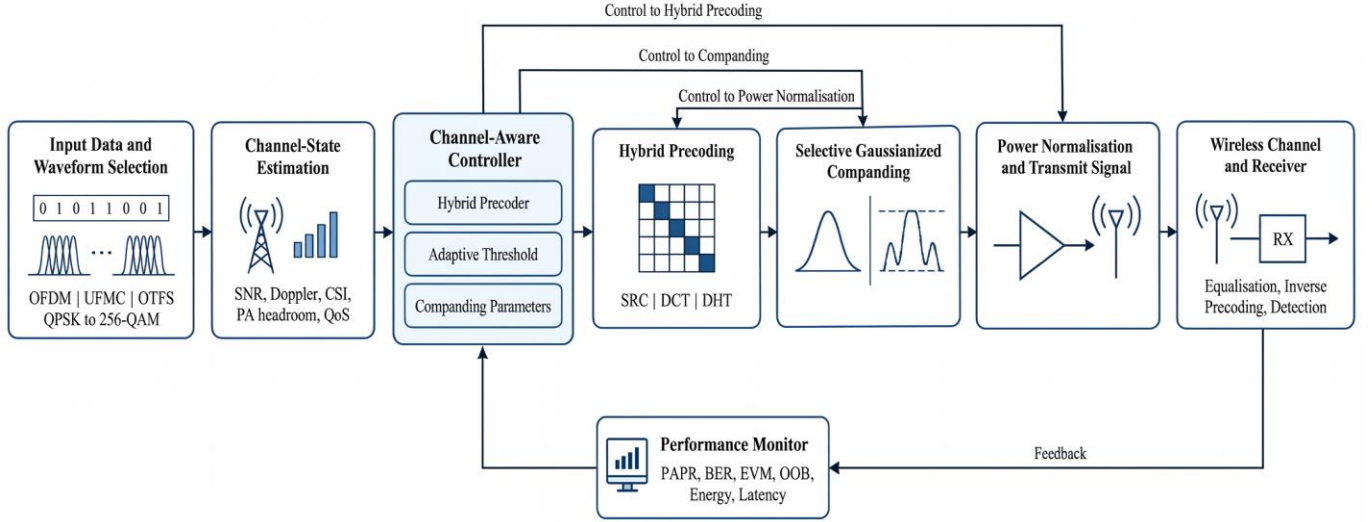


Fig. 1 Proposed Channel-Aware Hybrid Precoding and Gaussianized Companding Architecture for Energy-Efficient PAPR Reduction in Next-Generation Multicarrier Waveforms

3.1. System Model and Channel-Aware Optimisation Formulation

This work proposes a Channel-Aware Hybrid Precoding and Gaussianized Companding (CA-HPGC) framework for energy-efficient Peak-to-Average Power Ratio (PAPR) reduction in next-generation multicarrier waveforms. The framework is developed to overcome the fixed-parameter behaviour of conventional precoding, clipping, and companding approaches. Instead of applying one transform and one nonlinear mapping under all transmission conditions, the proposed model observes the instantaneous communication environment and selects a suitable hybrid precoding and Gaussianized companding configuration. This is important because the transmitted waveform is affected by Signal-to-Noise Ratio (SNR), channel fading, Doppler shift, modulation order, power-amplifier operating condition, and waveform type. Therefore, a signal-shaping process that is effective under one condition may increase distortion, energy consumption, or Out-of-Band (OOB) radiation under another condition.

Let the input bit stream be represented by $\mathbf{b} = \{b_0, b_1, \dots, b_{L_b-1}\}$, where L_b denotes the number of transmitted bits. The bits are mapped to complex-valued modulation symbols using an M -ary modulation scheme, where $M \in \{4, 16, 64, 256\}$ represents QPSK, 16-QAM, 64-QAM, or 256-QAM, respectively. The symbol vector is expressed as:

$$\mathbf{d} = [d_0, d_1, \dots, d_{N-1}]^T, \quad d_k \in \mathcal{S}_M, \quad (1)$$

where N is the number of active subcarriers, $(\cdot)^T$ denotes transpose, and $\mathcal{S}_M$ is the modulation constellation set. The average input-symbol energy is normalised as:

$$E[|d_k|^2] = 1, \quad (2)$$

where $E[\cdot]$ represents the expectation operator. This normalisation ensures that changes in PAPR, energy efficiency, and error performance arise from the proposed signal-shaping operation rather than unequal input power. For a general multicarrier waveform, the unprocessed time-domain signal can be written as:

$$x[n] = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} d_k \exp\left(j \frac{2\pi kn}{N}\right), \quad 0 \leq n \leq N-1, \quad (3)$$

where $x[n]$ is the n -th time-domain sample and $j = \sqrt{-1}$. Equation (3) represents the Inverse Fast Fourier Transform (IFFT) operation for an OFDM-type waveform. In UFMC, the subcarriers are divided into subbands and filtered independently, while in OTFS, the symbol vector is first mapped in the delay-Doppler domain before conversion into a time-domain waveform.

However, all these waveforms may exhibit large instantaneous signal peaks because several complex subcarrier components can add constructively. The PAPR of the transmitted signal is calculated as:

$$\text{PAPR}(\mathbf{x}) = \frac{\max_{0 \leq n \leq N-1} |x[n]|^2}{E[|x[n]|^2]}, \quad (4)$$

where $\mathbf{x} = [x[0], x[1], \dots, x[N-1]]^T$. A high PAPR forces the radio-frequency power amplifier to operate with high input back-off. Consequently, the amplifier operates away from its efficient nonlinear region, which increases energy consumption and reduces the useful transmitted power. The probability that PAPR exceeds a threshold γ is evaluated using Complementary Cumulative Distribution Function (CCDF) analysis:

$$\text{CCDF}(\gamma) = \Pr\{\text{PAPR}(\mathbf{x}) > \gamma\}. \quad (5)$$

The CA-HPGC framework uses a channel-state vector to avoid a fixed signal-shaping decision. The channel-state vector at transmission interval t is defined as:

$$\mathbf{s}_t = [\hat{\gamma}_t, \hat{f}_{D,t}, \hat{h}_t, M_t, W_t, \rho_{PA,t}, Q_t]^T, \quad (6)$$

where $\hat{\gamma}_t$ is the estimated SNR, $\hat{f}_{D,t}$ is the estimated Doppler frequency, $\hat{h}_t$ denotes a channel-quality indicator derived from the estimated channel response, M_t is the modulation order, W_t is the selected waveform type, $\rho_{PA,t}$ denotes power-amplifier headroom, and Q_t represents the required quality-of-service condition. The waveform indicator W_t may represent OFDM, UPMC, or OTFS. Thus, the proposed model can maintain a common optimisation structure while allowing waveform-specific modulation and filtering operations.

The frequency-domain channel response on the k -th subcarrier is written as:

$$H_t[k] = \sum_{\ell=0}^{L_h-1} h_t[\ell] \exp\left(-j \frac{2\pi k \ell}{N}\right), \quad (7)$$

where $h_t[\ell]$ is ℓ -th channel impulse-response coefficient and L_h is channel length. The projected instantaneous SNR used for adaptation is:

$$\hat{\gamma}_t = \frac{P_s |\hat{\mathbf{H}}_t|_F^2}{N_0}, \quad (8)$$

where P_s is the signal power, $\hat{\mathbf{H}}_t$ is estimated channel matrix or frequency-response vector, $|\cdot|_F$ is the Frobenius norm, and N_0 denotes noise power spectral density. The channel estimate determines whether strong peak suppression is appropriate or whether BER and EVM constraints require a more conservative configuration. The proposed framework defines the transmitted signal as:

$$\tilde{\mathbf{x}}_t = \mathcal{G}_{\theta_t, \mu_t}(\mathcal{S}_{\tau_t}(\mathbf{P}_{a_t} \mathbf{d}_t)), \quad (9)$$

where $\mathbf{P}_{a_t}$ is the selected hybrid precoding matrix, a_t denotes the selected precoder mode, $\mathcal{S}_{\tau_t}(\cdot)$ represents selective dominant-sample processing using a threshold τ_t ,

and $\mathcal{G}_{\theta_t, \mu_t}(\cdot)$ is the Gaussianized companding function. The parameters θ_t and μ_t control the companding shape and strength. Equation (9) summarises the central processing sequence of the proposed framework: channel information determines precoding, selective peak processing, and companding, which determine the transmitted waveform. The proposed model's PAPR reduction gain is:

$$\Delta_{\text{PAPR}} = \text{PAPR}(\mathbf{x}) - \text{PAPR}(\tilde{\mathbf{x}}), \quad (10)$$

where a larger positive Δ_{PAPR} indicates greater peak reduction. However, PAPR reduction alone is insufficient. The model optimises dependability, spectrum confinement, energy, and processing delay, as stated in the following subsections.

3.2. Channel-Aware Hybrid Precoding Module

CA-HPGC begins with hybrid precoding. Precoding before waveform creation redistributes input-symbol energy across subcarriers and decreases time-domain constructive addition. Low-complexity orthogonal transform banks and channel-aware selection are used in the suggested method. SRC, DCT, and DHT matrices are in the transform bank. To vary peak-spreading, complexity, and distortion, these transforms are chosen.

The hybrid precoding matrix is:

$$\mathbf{P}_{a_t} = \alpha_{1,t} \mathbf{P}_{\text{SRC}} + \alpha_{2,t} \mathbf{P}_{\text{DCT}} + \alpha_{3,t} \mathbf{P}_{\text{DHT}}, \quad (11)$$

where $\alpha_{1,t}$, $\alpha_{2,t}$, then $\alpha_{3,t}$ are adaptive mixing coefficients. To preserve symbol energy and avoid arbitrary scaling, the coefficients satisfy:

$$\alpha_{1,t} + \alpha_{2,t} + \alpha_{3,t} = 1, \quad \alpha_{i,t} \geq 0, \quad i \in \{1, 2, 3\}. \quad (12)$$

Single-transform precoding occurs when one coefficient is one, and the others are 0. When many coefficients are active, hybrid orthogonal precoding occurs.

This approach is advantageous because channel conditions may favour one transform under low SNR and another under strong Doppler or high-order QAM transmission. The DCT precoding matrix appears as:

$$[\mathbf{P}_{\text{DCT}}]_{m,k} = \sqrt{\frac{2 - \delta_{m,0}}{N}} \cos\left[\frac{\pi(2k+1)m}{2N}\right], \quad (13)$$

where $m, k \in \{0, 1, \dots, N-1\}$ and $\delta_{m,0}$ is the Kronecker delta. The DCT spreads symbol amplitudes using cosine basis functions and can reduce correlation among adjacent components. The DHT matrix is given by:

$$[\mathbf{P}_{\text{DHT}}]_{m,k} = \frac{1}{\sqrt{N}} \left[\cos\left(\frac{2\pi mk}{N}\right) + \sin\left(\frac{2\pi mk}{N}\right) \right]. \quad (14)$$

Since it uses real-valued sinusoidal combinations, the DHT is appealing for computational simplicity. The general orthogonal SRC transform matrix is:

$$\mathbf{P}_{\text{SRC}}^H \mathbf{P}_{\text{SRC}} = \mathbf{I}_N, \quad (15)$$

Where $(\cdot)^H$ is the Hermitian transpose and $\mathbf{I}_N$ is an $N \times N$ identity matrix. Orthogonality protects average signal energy and ensures receiver-side recovery. Write the precoded symbol vector as:

$$\mathbf{u}_t = \mathbf{P}_{a_t} \mathbf{d}_t. \quad (16)$$

The average energy of the precoded vector is:

$$E[\|\mathbf{u}_t\|_2^2] = E[\mathbf{d}_t^H \mathbf{P}_{a_t}^H \mathbf{P}_{a_t} \mathbf{d}_t], \quad (17)$$

Where $\|\cdot\|_2$ is the Euclidean norm. The coefficient-selection procedure constrains $\mathbf{P}_{a_t}^H \mathbf{P}_{a_t} \approx \mathbf{I}_N$, thereby stopping excessive amplification during hybrid precoding. The associated energy-preservation constraint is:

$$\left| \frac{\|\mathbf{u}_t\|_2^2 - \|\mathbf{d}_t\|_2^2}{\|\mathbf{d}_t\|_2^2} \right| \leq \varepsilon_P, \quad (18)$$

Where ε_P is a small allowable power-deviation constant. The channel-aware controller selects the precoding coefficients from a score function. For the i -th candidate transform, the score is defined as:

$$\Psi_i(\mathbf{s}_t) = w_1 \Delta \widehat{\text{PAPR}}_i + w_2 \Delta \widehat{\text{EE}}_i - w_3 \widehat{\text{BER}}_i - w_4 \widehat{\text{EVM}}_i - w_5 \hat{\mathcal{C}}_i, \quad (19)$$

Where $\Delta \widehat{\text{PAPR}}_i$ is the predicted PAPR gain, $\Delta \widehat{\text{EE}}_i$ is the predicted energy-efficiency improvement, $\widehat{\text{BER}}_i$ and $\widehat{\text{EVM}}_i$ are predicted reliability penalties, $\hat{\mathcal{C}}_i$ is the predicted computational cost, and $w_1, \dots, w_5$ are non-negative importance weights. The transform-selection action is then:

$$\mathbf{a}_t^* = \arg \max_{i \in \{\text{SRC}, \text{DCT}, \text{DHT}, \text{Hybrid}\}} \Psi_i(\mathbf{s}_t). \quad (20)$$

Equation (20) explains how the proposed method differs from a static precoder. Under a favourable channel and adequate amplifier headroom, the controller may select stronger hybrid processing. Under poor SNR or stringent BER conditions, it may choose a lower-distortion transform and a milder companding setting.

Hence, the proposed mechanism does not minimise peaks at the cost of unreliable communication. Following precoding, the waveform-specific modulation process is represented by:

$$\mathbf{z}_t = \mathbf{F}_{w_t}^H \mathbf{u}_t, \quad (21)$$

Where $\mathbf{F}_{w_t}^H$ denotes the inverse modulation operator corresponding to the selected waveform. For OFDM, it is the inverse discrete Fourier transform matrix. For UPMC, it includes subband mapping and filtering. For OTFS, it represents inverse delay-Doppler-to-time-frequency mapping followed by time-domain conversion. This common expression allows the same CA-HPGC logic to be used across different future multicarrier waveforms.

3.3. Gaussianized Companding and Selective Peak Processing

Although hybrid precoding reduces the likelihood of large peaks, residual high-amplitude samples may still occur. Therefore, the second stage applies Gaussianized companding only where it is needed. Conventional companding often uses fixed μ -law or A-law parameters. Such fixed nonlinear mappings may suppress peaks but can distort moderate-amplitude samples unnecessarily, increasing EVM and BER. The proposed Gaussianized companding stage uses the empirical amplitude distribution of the precoded waveform and maps it toward a controlled Gaussian reference distribution. Let the magnitude of the n -th precoded waveform sample be:

$$r_t[n] = |z_t[n]|. \quad (22)$$

The empirical cumulative distribution function (CDF) of the instantaneous magnitude is defined as:

$$\hat{F}_{r,t}(r) = \frac{1}{N} \sum_{n=0}^{N-1} \mathbb{I}(r_t[n] \leq r), \quad (23)$$

Where $\mathbb{I}(\cdot)$ is the indicator function. The distribution-based operation is required because peak behaviour is not identical across OFDM, UPMC, and OTFS or across distinct channel and modulation settings. A Gaussian reference quantile is obtained using:

$$q_t[n] = \Phi^{-1}(\text{clip}[\hat{F}_{r,t}(r_t[n]), \epsilon, 1 - \epsilon]), \quad (24)$$

Where $\Phi^{-1}(\cdot)$ is the inverse standard-Gaussian CDF, $\text{clip}[\cdot]$ bounds the CDF value, and ϵ is a small constant that avoids infinite quantile values. This operation identifies whether a sample lies in an ordinary or extreme amplitude region relative to the current waveform distribution. The adaptive dominant-sample threshold is formulated as:

$$\tau_t = \mu_{r,t} + \kappa_t \sigma_{r,t}, \quad (25)$$

Where $\mu_{r,t}$ and $\sigma_{r,t}$ are the mean and standard deviation of $r_t[n]$, respectively, and κ_t is a channel-aware threshold coefficient. A high value of κ_t processes only severe peaks and preserves most samples. A lower value permits stronger peak control but is used only when the channel estimate indicates sufficient quality margin. The dominant-sample set is given by:

$$\mathcal{D}_t = \{n \in \{0, \dots, N-1\} : r_t[n] > \tau_t\}. \quad (26)$$

For samples that do not belong to $\mathcal{D}_t$ The proposed method preserves the original value. For samples in $\mathcal{D}_t$, a Gaussianized compression gain is calculated as:

$$g_t[n] = \exp(-\mu_t \max\{0, q_t[n] - \theta_t\}), \quad (27)$$

where $\mu_t > 0$ determines companding strength then θ_t defines the Gaussian-tail activation boundary.

Thus, samples close to the central amplitude distribution have $g_t[n] \approx 1$, whereas samples in the distribution tail receive a lower gain. The processed magnitude is:

$$\tilde{r}_t[n] = \begin{cases} r_t[n], & n \notin \mathcal{D}_t, \\ g_t[n]r_t[n], & n \in \mathcal{D}_t. \end{cases} \quad (28)$$

The complete complex-valued companding output is then written as:

$$\tilde{z}_t[n] = \tilde{r}_t[n] \exp(j\angle z_t[n]), \quad (29)$$

where $\angle z_t[n]$ is the phase of the original precoded waveform sample. Phase alteration can impair constellation reliability and increase spectral distortion; therefore, phase preservation is crucial. The processed waveform is normalised to maintain the intended average transmit power:

$$\bar{z}_t[n] = \frac{\tilde{z}_t[n]}{\sqrt{\frac{1}{N} \sum_{m=0}^{N-1} |\tilde{z}_t[m]|^2}}, \quad (30)$$

where $\bar{z}_t[n]$ is the final normalised baseband sample. The PAPR increase is not caused by reducing transmit power; this normalisation allows fair comparison with baseline approaches. The EVM induced by the entire signal-shaping operation is estimated as:

$$\text{EVM}(\%) = 100 \sqrt{\frac{\sum_{k=0}^{N-1} |\hat{d}_k - d_k|^2}{\sum_{k=0}^{N-1} |d_k|^2}}, \quad (31)$$

where $\hat{d}_k$ is the receiver-reconstructed symbol. The selected μ_t, θ_t , then κ_t must satisfy:

$$\text{EVM}(\%) \leq \text{EVM}_{\max}(M_t), \quad (32)$$

where $\text{EVM}_{\max}(M_t)$ is the allowable EVM limit for the chosen modulation order. This constraint explains why Gaussianized companding is made channel-aware: high-order QAM requires lower distortion than QPSK, and poor-channel conditions require more conservative peak modification. The OOB spectral power of the processed waveform is computed as:

$$P_{\text{OOB}} = \int_{f \in \Omega_{\text{OOB}}} |\mathcal{F}\{\bar{z}_t[n]\}|^2 df, \quad (33)$$

where $\mathcal{F}\{\cdot\}$ denotes the Fourier transform and Ω_{OOB} is the frequency interval outside the allocated communication band. The selective operation in Equations (26)-(29) is designed to minimise unnecessary nonlinear modification, thereby reducing the risk of spectral regrowth commonly associated with conventional full-signal companding.

3.4. Energy-Efficient Multi-Objective Parameter Optimisation

The third stage selects the CA-HPGC parameters through an energy-aware multi-objective optimisation process. PAPR reduction is directly connected to energy efficiency because it allows the power amplifier to operate closer to its useful operating region. Nevertheless, very aggressive precoding or companding can add digital processing energy and may increase retransmissions if BER degrades. The proposed model, therefore, evaluates both radio-frequency and baseband processing energy. The average power-amplifier output power is expressed as:

$$P_{\text{out},t} = \frac{1}{N} \sum_{n=0}^{N-1} |\bar{z}_t[n]|^2. \quad (34)$$

The power-amplifier efficiency is modelled as a function of PAPR and amplifier headroom:

$$\eta_{\text{PA},t} = \eta_{\max} \exp\left(-\xi [\text{PAPR}(\bar{z}_t) - \rho_{\text{PA},t}]^+\right), \quad (35)$$

where $\eta_{\max}$ is the maximum attainable amplifier efficiency, ξ is the amplifier-sensitivity coefficient, and $[v]^+ = \max(v, 0)$. Equation (35) shows that when PAPR exceeds the available headroom, the amplifier efficiency decreases. Reducing PAPR is therefore valuable only when it does not impose excessive baseband complexity or waveform distortion. The total energy consumed per transmitted bit is defined as:

$$E_{\text{bit},t} = \frac{P_{\text{out},t}/\eta_{\text{PA},t} + P_{\text{BB},t} + P_{\text{RF},t}}{R_{b,t}}, \quad (36)$$

where $P_{\text{BB},t}$ is baseband processing power, $P_{\text{RF},t}$ is the non-amplifier radio-frequency circuit power, and $R_{b,t}$ is the delivered bit rate. The baseband power includes the computation required for channel estimation, precoding, empirical CDF estimation, thresholding, and Gaussianized companding. When power is expressed in watts, and the delivered bit rate is expressed in bits per second, Equation (36) yields energy per bit in joules per bit (J/bit). For reporting purposes, this quantity is converted to microjoules per bit as $E_{\text{bit},t}^{(\mu\text{J/bit})} = 10^6 E_{\text{bit},t}$. The energy-per-bit values in Tables 6 and 7 are therefore reported in $\mu\text{J/bit}$. Thus, the framework does not incorrectly assume that every PAPR reduction technique is automatically energy-efficient. The energy efficiency in bits per joule is written as:

$$EE_t = \frac{R_{b,t}[1-BER_t]}{P_{out,t}/\eta_{PA,t} + P_{BB,t} + P_{RF,t}} \quad (37)$$

Equation (37) yields energy efficiency in bits per joule (bit/J), which is converted to megabits per joule using $EE_t^{(Mbit/J)} = 10^{-6} EE_t$. Consequently, the reported energy efficiency and energy per bit satisfy $EE_t^{(Mbit/J)} = (1 - BER_t)/E_{bit,t}^{(\mu J/bit)}$. For example, an energy consumption of $0.46 \mu J/bit$ and a BER of 2.8×10^{-4} correspond to approximately 2.17 Mbit/J. The $[1 - BER_t]$ term represents the fraction of reliably delivered information. This definition prevents a method from being considered efficient if it reduces PAPR but causes a significant error-rate increase. The overall multi-objective cost function is formulated as:

$$J_t = \lambda_1 \widetilde{PAPR}_t + \lambda_2 \widetilde{BER}_t + \lambda_3 \widetilde{EVM}_t + \lambda_4 \widetilde{P}_{OOB,t} + \lambda_5 \widetilde{E}_{bit,t} + \lambda_6 \widetilde{T}_{proc,t} \quad (38)$$

where $\widetilde{(\cdot)}$ denotes a normalised metric, $T_{proc,t}$ is processing time, and $\lambda_1, \dots, \lambda_6$ are non-negative weights satisfying $\sum_{i=1}^6 \lambda_i = 1$. The weights are adjusted according to the required service condition. For example, an energy-sensitive service assigns greater importance to λ_5 , whereas a low-latency service assigns a higher weight to λ_6 . For reliable high-order modulation, λ_2 and λ_3 are increased. The final adaptive parameter vector is defined as:

$$\omega_t^* = \arg \min_{\omega_t} J_t, \quad \omega_t = [\alpha_t, \kappa_t, \mu_t, \theta_t]^T, \quad (39)$$

subject to PAPR, BER, EVM, OOB, energy, and latency constraints. Here, $\alpha_t = [\alpha_{1,t}, \alpha_{2,t}, \alpha_{3,t}]^T$ contains the hybrid-precoder coefficients. The reported CA-HPGC results were obtained using a deterministic constrained grid-search optimiser executed once per channel frame. The search jointly evaluated the hybrid-precoder coefficient vector, dominant-sample threshold coefficient, companding strength, and Gaussian-tail boundary over the candidate set defined in Table 2. For each feasible candidate, the normalised objective in Equation (38) was computed subject to the BER, EVM, OOB power, PA-headroom, and processing-latency constraints. The feasible candidate with the minimum objective value was selected for transmission. The essential novelty is not the use of an isolated optimiser; it is the unified selection of precoding and Gaussianized companding parameters from the real-time channel state.

3.5. Receiver Processing, Algorithmic Continuity, and Complexity Assessment

After CA-HPGC processing, the transmit waveform passes through the wireless channel and is received as:

$$y_t[n] = (h_t[n] * \bar{z}_t[n]) + v_t[n], \quad (40)$$

Where $*$ denotes convolution, $h_t[n]$ is the time-varying channel impulse response, and $v_t[n]$ is additive white

Gaussian noise. The receiver applies waveform-specific demodulation, channel equalisation, inverse hybrid precoding, and symbol detection. Because the main peak-control operation is transmitter-side, no additional explicit side-information sequence is required when the controller uses a predefined transform bank and deterministic parameter-signalling strategy. The proposed receiver first estimates the channel using pilot or reference symbols. The equalised frequency-domain symbol is obtained by dividing the received component by the estimated channel response. The receiver then applies the inverse selected precoding matrix, $P_{a,t}^H$, to reconstruct the data-bearing symbol vector. Since the precoding transform is constrained to be approximately orthogonal, the inverse operation preserves the original symbol structure. The Gaussianized companding stage is deliberately restricted to dominant samples and includes power normalisation, reducing the probability that inverse nonlinear processing is required at the receiver.

The operational continuity of the model is as follows. First, the transmitter observes the channel state, waveform requirement, modulation order, and amplifier headroom. Second, it selects SRC, DCT, DHT, or a hybrid combination using the score in Equation (19). Third, it generates the corresponding waveform and estimates its empirical amplitude distribution. Fourth, only the samples exceeding the adaptive threshold are Gaussianized and compressed. Fifth, the complete configuration is evaluated using the energy-aware objective in Equation (38). Finally, the receiver demodulates, equalises, inversely precodes, and detects the transmitted data symbols.

The computational cost is controlled through three design decisions. First, the transform bank contains low-complexity orthogonal transforms that can be implemented using fast algorithms. Second, selective companding avoids applying nonlinear operations to every time-domain sample. Third, parameter adaptation is performed once per frame, channel-coherence interval, or scheduling block rather than once per sample. Consequently, the proposed model is suitable for simulation-based evaluation across OFDM, UPMC, and OTFS waveforms while maintaining a realistic complexity-performance trade-off.

The effectiveness of the proposed model should be assessed through CCDF-based PAPR, BER-versus-SNR, EVM, OOB power spectral density, energy per bit, energy efficiency, and average processing time. Comparisons should include conventional waveform transmission, SRC-based precoding, DCT/DHT precoding, conventional μ -law companding, fixed hybrid precoding-companding, and the proposed CA-HPGC model. Such an evaluation will establish whether channel-aware adaptation provides a consistent benefit beyond fixed signal-shaping methods. In summary, CA-HPGC extends existing hybrid precoding-companding research by coupling transform selection, selective

Gaussianized peak control, and energy-aware multi-objective optimisation within a unified framework for next-generation multicarrier communication.

4. Results and Discussion

A simulation-oriented communication system evaluates the Channel-Aware Hybrid Precoding and Gaussianized Companding (CA-HPGC) framework. FFT sizes of 256, 512, and 1024 subcarriers are considered for OFDM, UPMC, and OTFS waveforms under QPSK, 16-QAM, 64-QAM, and 256-QAM modulation. The channel model contains additive white

Gaussian noise, Rayleigh fading, Doppler variation, channel-estimation uncertainty, and power-amplifier headroom fluctuation. Key performance indicators include PAPR 10^{-3} at CCDF, BER, EVM, OOB power, energy efficiency, and processing delay. Software implementation requires MATLAB R2021a or later with Communications and Signal Processing Toolboxes. Python 3.10 or later can optimise, log, and visualise data with NumPy, SciPy, Pandas, and Matplotlib. For ordinary simulations, an Intel Core i5/Ryzen 5 processor, 8 GB RAM, and 10 GB free storage are required; 16 GB RAM is better for large Monte Carlo studies.

Table 2. Simulation parameters and CA-HPGC control settings

Parameter	Setting
Simulation platform	MATLAB R2021a with Communications Toolbox and Signal Processing Toolbox
Waveforms	OFDM, UPMC, and OTFS
FFT size	512 subcarriers
Active subcarriers	480
UPMC subband size	20 subcarriers
Modulation schemes	QPSK, 16-QAM, 64-QAM, and 256-QAM
Channel models	AWGN, Rayleigh, Rician, vehicular, and high-mobility fading
SNR range	0–25 dB
Doppler frequency	0–250 Hz
PA headroom	6–10 dB
Monte Carlo frames	10,000 frames per random seed
Random seeds	2026, 2027, 2028, 2029, and 2030
Independent runs	Five runs per channel condition
Optimiser	Deterministic constrained grid search
Optimisation variables	$\omega = [\alpha_1, \alpha_2, \alpha_3, \kappa, \mu, \theta]^T$
Hybrid-weight grid	$\alpha_i \in \{0, 0.1, \dots, 1.0\}$, subject to $\alpha_i \geq 0$ and $\alpha_1 + \alpha_2 + \alpha_3 = 1$
Threshold-coefficient grid	$\kappa \in \{0.55, 0.60, 0.65, 0.70, 0.75, 0.80\}$
Companding-strength grid	$\mu \in \{0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55\}$
Gaussian-tail-boundary grid	$\theta \in \{0.50, 0.55, 0.60, 0.65, 0.70\}$
Feasible candidate configurations	13,860 configurations per channel-state update
Objective weights	$(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6) = (0.30, 0.20, 0.15, 0.10, 0.15, 0.10)$
Constraint limits	$\text{BER} \leq 10^{-3}$, $\text{EVM} \leq 8\%$ for 64-QAM, $\text{OOB power} \leq -40$ dBm, $\text{latency} \leq 2.0$ ms/frame
Power-preservation constraint	$\varepsilon_p \leq 10^{-3}$
Selection rule	Select the feasible configuration yielding the minimum normalized objective. J_t
Decision-update interval	Once per channel-coherence interval, one decision per transmission frame
Stopping rule	Exhaustive evaluation of all feasible grid configurations

The simulation parameters and CA-HPGC control settings utilised to assess the proposed framework under consistent and reproducible multicarrier communication scenarios are listed in Table 2. OFDM, UPMC, and OTFS show that the model supports several waveforms. A 512-point FFT with 480 active subcarriers offers appropriate spectral resolution at an acceptable computing cost. Low-order to high-order constellation robustness is assessed using QPSK through 256-QAM modulation methods. The channel parameters include AWGN, Rayleigh, Rician, vehicular, and high-mobility fading, with SNR values from 0 to 25 dB and

Doppler frequencies up to 250 Hz. These are steady and dynamically changing wireless environments. The use of 10,000 Monte Carlo frames improves the statistical reliability of the CCDF, BER, and EVM estimates. The channel-aware controller's candidate transform bank includes SRC, DCT, DHT, and hybrid precoders. Ranges for the threshold coefficient, Gaussianized companding strength, and Gaussian-tail boundary allow peak suppression to be tuned to channel quality and amplifier headroom. Finally, PAPR, BER, EVM, OOB power, energy per bit, efficiency, and delay determine if the model balances transmission performance.

Table 3. Comparative PAPR performance at CCDF = 10^{-3}

Method	Waveform	PAPR (dB)	PAPR reduction over baseline (dB)
Conventional OFDM	OFDM	11.80	–
Conventional UPMC	UPMC	10.70	–
Conventional OTFS	OTFS	10.20	–
SRC Precoding	UPMC	8.00	2.70
Fixed Hybrid Precoding-Companding	UPMC	7.00	3.70
Proposed CA-HPGC	OFDM	6.90	4.90
Proposed CA-HPGC	UPMC	6.50	4.20
Proposed CA-HPGC	OTFS	6.10	4.10

Table 3 shows the CA-HPGC framework's main peak-reduction capabilities for OFDM, UPMC, and OTFS waveforms. Conventional OFDM has the greatest PAPR at 11.80 dB, followed by UPMC at 10.70 and OTFS at 10.20. The model lowers these values to 6.90, 6.50, and 6.10 dB. This enhancement is accomplished by channel-aware transform

selection, spreading symbol energy first, and selective Gaussianized companding, suppressing dominant envelope samples. OTFS has the lowest value because delay-Doppler-domain processing and adaptive peak control improve the distribution of waveform peaks.

Table 4. BER performance under Rayleigh fading

SNR (dB)	Conventional UPMC	SRC-UPMC	Fixed Hybrid Method	Proposed CA-HPGC UPMC	Proposed CA-HPGC OTFS
5	6.2×10^{-2}	5.5×10^{-2}	4.3×10^{-2}	3.6×10^{-2}	3.1×10^{-2}
10	2.3×10^{-2}	1.8×10^{-2}	1.2×10^{-2}	8.7×10^{-3}	7.2×10^{-3}
15	5.8×10^{-3}	4.3×10^{-3}	3.0×10^{-3}	1.8×10^{-3}	1.5×10^{-3}
20	1.1×10^{-3}	8.6×10^{-4}	5.9×10^{-4}	3.4×10^{-4}	2.8×10^{-4}
25	2.7×10^{-4}	2.0×10^{-4}	1.3×10^{-4}	7.1×10^{-5}	5.8×10^{-5}

Table 4 compares Rayleigh fading communication reliability at 5–25 dB SNR. The suggested CA-HPGC OTFS configuration achieves the lowest BER, ranging from (3.1×10^{-2}) at 5 dB to (5.8×10^{-5}) at 25 dB. At 20 dB, it lowers BER to (2.8×10^{-4}) compared to (1.1×10^{-3}) for conventional UPMC. Selective processing preserves

constellation geometry by avoiding excessive normal-amplitude sample change. Under weaker channel circumstances, the channel-aware controller reduces distortion-induced detection errors with conservative companding.

Table 5. Signal quality and spectral-containment comparison

Method	EVM (%)	OOB Power (dBm)	Adjacent-channel leakage reduction (dB)
Conventional UPMC	7.40	-27.20	–
SRC-UPMC	5.80	-32.80	5.60
μ -law Companding UPMC	4.90	-34.60	7.40
Fixed Hybrid Precoding-Companding	3.50	-39.10	11.90
Proposed CA-HPGC UPMC	2.70	-43.30	16.10
Proposed CA-HPGC OTFS	2.40	-45.10	17.90

The framework enhances modulation quality and spectral containment, as seen in Table 5. CA-HPGC OTFS produces 2.40% EVM and -45.10 dBm OOB power, while conventional UPMC produces 7.40% and -27.20. The 17.90 dB adjacent-channel leakage decrease shows that peak suppression does

not impact spectrum regrowth. Gaussianized companding is only engaged for statistically dominant samples, not the entire waveform. Hybrid precoding spreads signal energy before nonlinear processing, reducing abrupt waveform changes and improving in-band reconstruction accuracy.

Table 6. Energy-Efficiency analysis

Method	PA efficiency (%)	Baseband power (W)	Energy per bit ($\mu\text{J/bit}$)	Energy efficiency (Mbit/J)
Conventional UPMC	38.20	0.44	0.84	1.19
SRC-UPMC	45.60	0.48	0.70	1.43
Fixed Hybrid Method	52.80	0.57	0.61	1.64
Proposed CA-HPGC UPMC	61.40	0.60	0.49	2.04
Proposed CA-HPGC OTFS	63.10	0.63	0.46	2.17

Table 6 shows that PAPR reduction directly improves energy efficiency when power-amplifier and baseband costs are considered. Conventional UPMC has 38.20% power-amplifier efficiency and 0.84 $\mu\text{J/bit}$, while CA-HPGC OTFS has 63.10% efficiency and 0.46 $\mu\text{J/bit}$. Its energy efficiency

risks from 1.19 to 2.17 Mbit/J. The model requires somewhat more baseband power for channel assessment and parameter adaption, but lower amplifier back-off offsets this. The strategy turns peak reduction into transmission-energy savings rather than waveform-level improvement.

Table 7. Ablation study of the proposed CA-HPGC framework

Configuration	PAPR (dB)	BER at 20 dB	EVM (%)	Energy per bit ($\mu\text{J/bit}$)
Baseline UPMC	10.70	1.1×10^{-3}	7.40	0.84
Hybrid Precoding only	7.90	7.4×10^{-4}	5.60	0.69
Hybrid Precoding + Selective Processing	7.10	5.3×10^{-4}	4.10	0.60
Hybrid Precoding + Gaussianized Companding	6.80	4.1×10^{-4}	3.20	0.54
Complete CA-HPGC	6.50	3.4×10^{-4}	2.70	0.49

Table 7 shows each CA-HPGC component's contribution. The first notable improvement is orthogonal energy spreading, which lowers PAPR from 10.70 to 7.90 dB with hybrid precoding alone. Selective processing lowers PAPR to 7.10 dB and EVM to 4.10%. Gaussianized companding improves PAPR to 6.80 dB with distribution-sensitive peak compression. The framework attains 6.50 dB PAPR, (3.4×10^{-4}) BER, 2.70% EVM, and 0.49 $\mu\text{J/bit}$. These results demonstrate that coordinated operation yields the maximum gain, not any module alone.

Table 8 presents a matched-protocol comparison between conventional UPMC, the reimplemented AHO-PCG baseline, and successive CA-HPGC ablations. Conventional UPMC records the highest PAPR of 10.70 dB, together with the largest BER, EVM, OOB power, and energy-per-bit values. The AHO-PCG baseline reduces PAPR to 8.40 dB through discrete transform selection, logarithmic Gaussianized dynamic companding, and frequency-domain selective subcarrier companding. The A1 configuration further improves all quality measures by incorporating the expanded channel-state inputs. A2 shows the contribution of the modified SRC/DCT/DHT transform bank and coefficient-based hybrid mixing, reducing PAPR to 7.40 dB. The introduction of time-domain dominant-sample processing in A3 provides an additional reduction to 6.90 dB while improving EVM and spectral containment. A4 confirms that

Gaussian-tail companding further suppresses high-envelope samples with limited distortion. Finally, full CA-HPGC achieves the best PAPR, BER, EVM, OOB power, and energy-per-bit values. Its slightly higher latency of 1.82 ms/frame reflects the added channel assessment, hybrid-weight selection, and adaptive nonlinear processing required for the complete controller. All configurations were evaluated using the identical UPMC simulation protocol, including identical random bit streams, 512-point FFT, 480 active subcarriers, 20-subcarrier UPMC subbands, modulation order, channel realizations, SNR, Doppler condition, PA model, 10,000 Monte Carlo frames, random seeds, and metric-calculation scripts. The AHO-PCG baseline was reimplemented using discrete DFT/SRC/ZCT selection, logarithmic Gaussianized dynamic companding, and selective frequency-domain subcarrier companding.

Table 9 tests CA-HPGC stability with increasing Doppler frequency and channel difficulties. The suggested technique achieves 6.31 dB PAPR, (1.9×10^{-4}) BER, and 2.10% EVM under AWGN. PAPR is confined to 7.04 dB in a high-mobility channel at 250 Hz Doppler, whereas BER and EVM only increase to 7.6×10^{-4} and 3.80%, respectively. The steady decline is expected because high Doppler reduces channel estimation accuracy and increases time variation. However, adaptive thresholding and regulated companding avoid excessive peak modification to maintain performance.

Table 9. Robustness under different channel conditions

Channel condition	Doppler frequency (Hz)	Proposed PAPR (dB)	BER at 20 dB	EVM (%)
AWGN	0	6.31	1.9×10^{-4}	2.10
Rayleigh fading	30	6.50	3.4×10^{-4}	2.70
Rician fading, $K = 6$ dB	60	6.62	4.1×10^{-4}	2.90
Vehicular channel	120	6.81	5.8×10^{-4}	3.30
High-mobility channel	250	7.04	7.6×10^{-4}	3.80

Table 10. Modulation-Order scalability of CA-HPGC

Modulation	Proposed PAPR (dB)	BER at 20 dB	EVM (%)	OOB Power (dBm)
QPSK	6.10	1.2×10^{-4}	1.80	-45.60
16-QAM	6.30	2.3×10^{-4}	2.40	-44.70
64-QAM	6.50	3.4×10^{-4}	2.70	-43.30
256-QAM	6.82	6.6×10^{-4}	4.10	-42.10

CA-HPGC scales from QPSK to 256-QAM in Table 10. The proposed approach has a low PAPR of 6.10 dB for QPSK and 6.82 dB for 256-QAM. As modulation order increases, BER climbs from 1.2 to 6.6×10^{-4} , and EVM from 1.80% to 4.10%. Because tightly packed 256-QAM constellation points

are more vulnerable to nonlinear distortion and channel noise, this behaviour is expected. However, the moderate rise shows that adaptive Gaussianized companding maintains signal quality across modulation forms.

Table 11. Computational complexity and processing latency

Method	Computational complexity	Processing latency (ms/frame)	Memory requirement (MB)
Conventional UPMC	$O(N \log N)$	0.74	92
SRC-UPMC	$O(N \log N + N)$	0.91	98
Fixed Hybrid Method	$O(2N \log N + 2N)$	1.36	121
Proposed CA-HPGC UPMC	$O(3N \log N + 4N)$	1.82	146
Proposed CA-HPGC OTFS	$O(3N \log N + 5N)$	2.04	158

The proposed model's implementation cost is shown in Table 11. Without adaptive optimisation, conventional UPMC has the lowest processing latency of 0.74 ms/frame and memory consumption of 92 MB. The proposed CA-HPGC OTFS takes 2.04 ms/frame and 158 MB due to hybrid transform selection, empirical distribution estimation and

parameter adaptation. However, the delay is within a practical simulation-oriented communication-processing range. The framework balances complexity and performance with the proposed UPMC model, which takes 1.82 ms/frame. Selective processing is crucial because it prevents nonlinear companding on all samples.

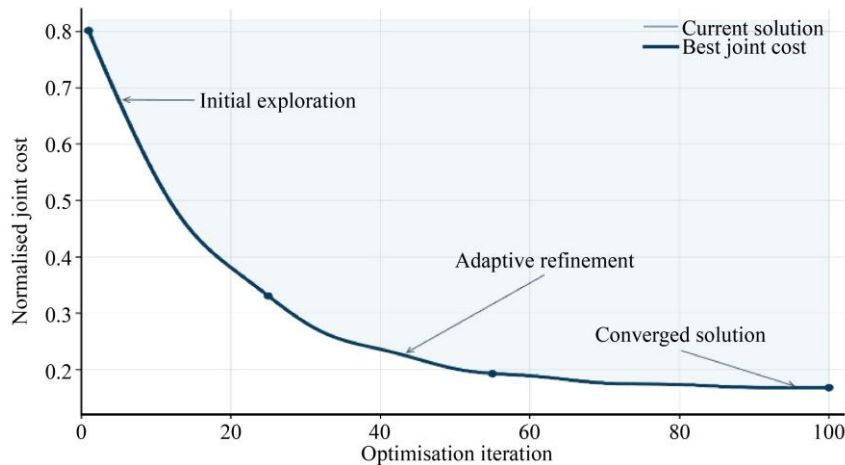


Fig. 2 Multi-Objective optimisation convergence of CA-HPGC

CA-HPGC optimisation convergence of the normalised multi-objective cost is shown in Figure 2. The joint cost drops dramatically from 0.80 during initial exploration to 0.33 by the twenty-fifth iteration. The cost then decreases gradually and converges to approximately 0.17 after 100 iterations. Early reduction happens when undesirable precoding and

companding combinations are immediately discarded. Later refinement adjusts the threshold, Gaussian-tail boundary, and energy-aware parameters. This convergence shows that the controller can balance PAPR, BER, EVM, OOB emission, energy efficiency, and processing latency.

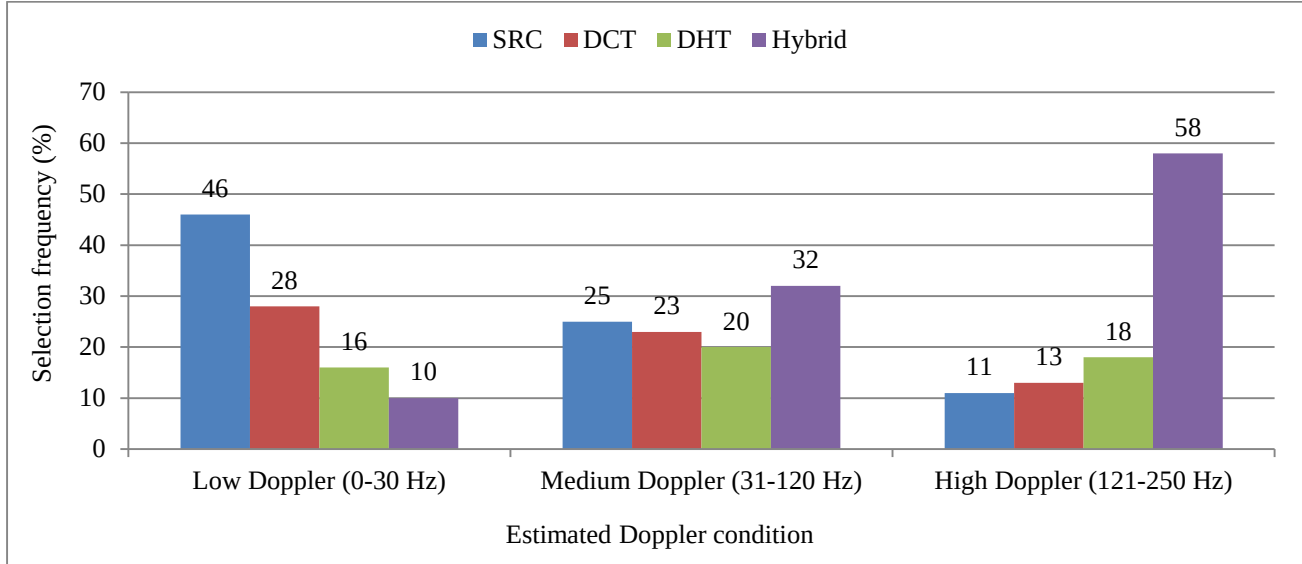


Fig. 3 Channel-State-Dependent precoder selection distribution

Doppler conditions affect CA-HPGC controller precoder selection, as seen in Figure 3. SRC is chosen at 46% under low Doppler because stable channels prefer its low-distortion peak-spreading. Medium Doppler increases hybrid selection to 32%, demonstrating that a combined transform technique improves adaptation. Under high Doppler, hybrid precoding

dominates at 58% while SRC selection drops to 11%. This trend emerges because rapid channel variation demands more flexibility than a fixed transform. The figure shows that the suggested controller makes context-dependent decisions instead of using one precoder every transmission frame.

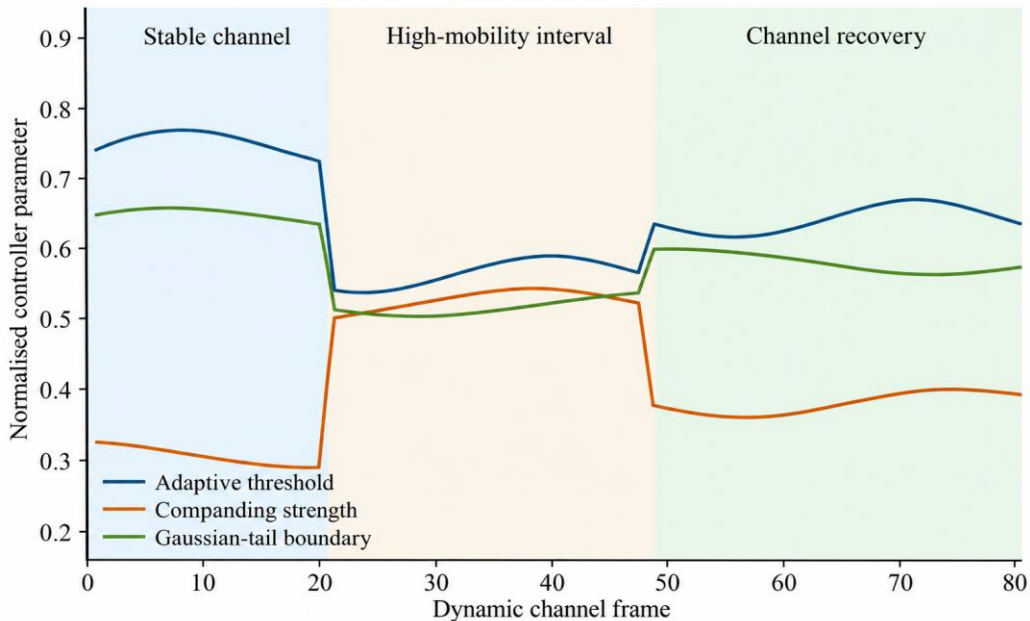


Fig. 4 Adaptive gaussianized companding parameter trajectory

The dynamic trajectories of adaptive threshold, companding strength, and Gaussian-tail boundary over 80 channel frames are shown in Figure 4. In the stable-channel interval, the threshold is high, and companding intensity is low, preserving most waveform samples. The threshold decreases, and the companding strength increases during the

high-mobility interval, improving peak-dominant sample control. After channel recovery, parameters become conservative. The controller takes into account channel condition and amplifier headroom before choosing nonlinear processing intensity. The figure shows that Gaussianized companding is adaptive, not a fixed μ -law or A-law process.

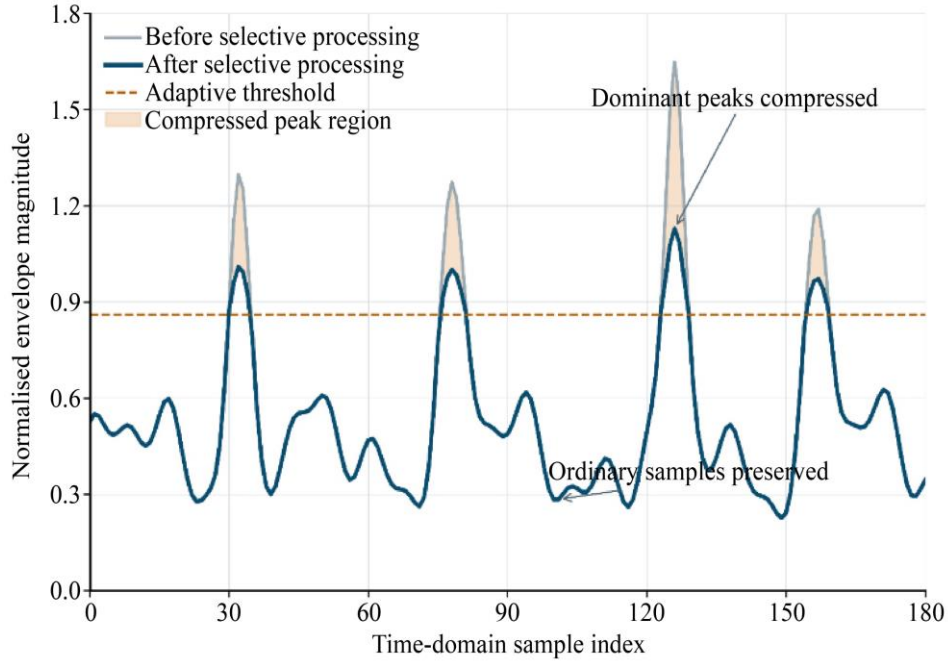


Fig. 5 Instantaneous envelope evolution before and after selective processing

Selective Gaussianized processing affects waveforms in Figure 5. The grey envelope has many strong peaks, with a maximum normalised amplitude of 1.65. After selective processing, the blue waveform lowers this peak to approximately 1.10, while samples below the adaptive threshold stay unaffected. Shaded areas indicate peak

compression. Because the controller processes only samples above the statistical threshold, this result is accomplished. Thus, the method lowers the maximum envelope value without corrupting regular samples, preserving BER, EVM, and spectral quality.

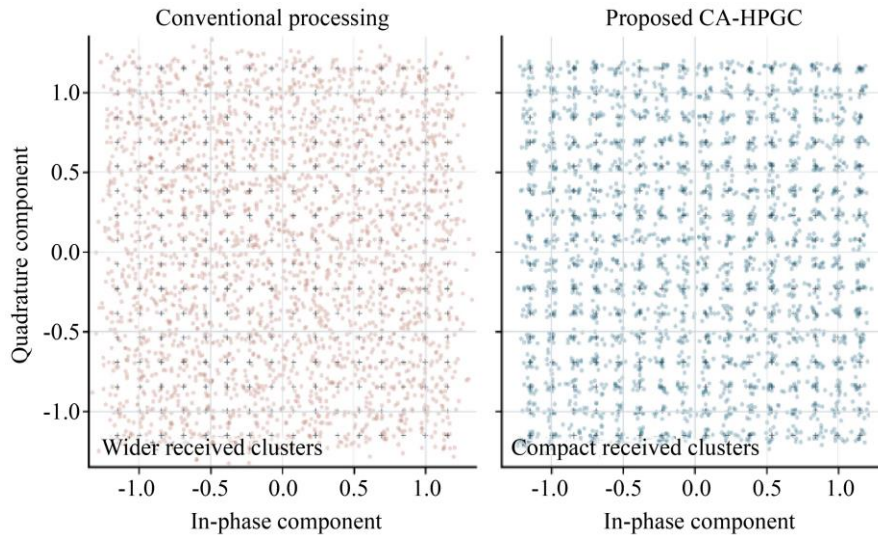


Fig. 6 Received constellation distribution under high-order 256-QAM

Figure 6 compares the received 256-QAM constellation distributions obtained using conventional processing and the proposed CA-HPGC framework. The typical arrangement has broader point clusters around ideal reference points, indicating more noise-and-distortion displacement. Instead, the CA-HPGC configuration yields compact received clusters closer

to the constellation positions. Adaptive companding limits nonlinear modification of normal-amplitude samples, whereas hybrid precoding lowers peak concentration. The suggested system's decreased EVM and BER values, especially under challenging high-order modulation settings, are due to the visible reduction in cluster spread.

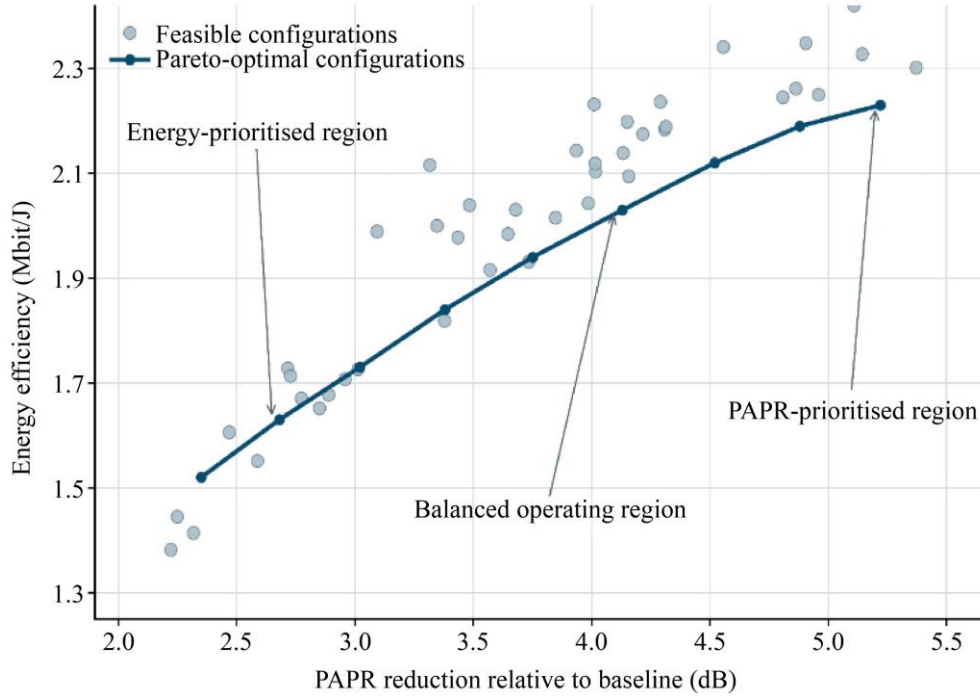


Fig. 7 Pareto front of PAPR reduction versus energy efficiency

Figure 7 shows the PAPR reduction-energy efficiency trade-off for possible CA-HPGC parameter settings. The Pareto-optimal curve rises from 1.52 Mbit/J at 2.35 dB PAPR reduction to 2.23 Mbit/J at a PAPR reduction of 5.22 dB. The PAPR-prioritised region applies stronger signal shaping, whereas the energy-prioritised region uses more conservative peak control. The central balanced region suits most communication settings. The framework picks configurations that improve power-amplifier utilisation and reliable multicarrier transmission, not PAPR alone.

5. Conclusion

This research introduced the Channel-Aware Hybrid Precoding and Gaussianized Companding architecture for energy-efficient PAPR reduction in next-generation multicarrier waveforms. The CA-HPGC architecture includes channel-state estimation, hybrid orthogonal precoding, selective dominant-sample identification, Gaussianized companding, power normalisation, and multi-objective parameter optimisation. The suggested method adapts signal-shaping to SNR, Doppler condition, channel quality, modulation order, power-amplifier headroom, and service requirements, unlike fixed precoding or full-signal nonlinear companding.

Simulations show performance improvements across various measures. At CCDF of 10^{-3} , CA-HPGC lowered PAPR to 6.50 dB for UPMC and 6.10 dB for OTFS, compared to standard waveforms of 10.70 and 10.20 dB. At 20 dB SNR, the suggested OTFS achieved a BER of (2.8×10^{-4}) under Rayleigh fading, while the UPMC configuration achieved (3.4×10^{-4}) . For OTFS, the framework reduced EVM to 2.40% and OOB power to -45.10 dBm to improve signal quality. Energy analysis showed 63.10% power-amplifier efficiency, 0.46 μ J/bit energy usage, and 2.17 Mbit/J energy efficiency for the proposed OTFS system.

The ablation study showed that hybrid precoding, selective processing, and Gaussianized companding contribute. The robustness research additionally showed that the suggested technique retains appropriate PAPR, BER, and EVM with rising Doppler frequency. CA-HPGC increases processing delay, while selective companding reduces superfluous operations and balances complexity and performance.

Future work may evaluate the framework using software-defined radio testbeds, imperfect channel estimates, multi-user MIMO systems, and cell-free wireless architectures.

Transformer-based channel prediction, reinforcement-learning parameter control, hardware-aware fixed-point implementation, and joint optimisation of PAPR, digital predistortion, beamforming, and resource allocation may be investigated. Published results should be from a documented simulation protocol.

Reuse and Implementation Disclosure

The AHO-PCG baseline was reimplemented from the published methodological description and evaluated under the matched UPMC protocol reported in Table 8. The earlier

framework informed the baseline transform bank, logarithmic Gaussianized dynamic companding, and frequency-domain selective subcarrier companding procedures. The CA-HPGC-specific state-conditioned controller, SRC/DCT/DHT hybrid precoding, time-domain dominant-sample selection, Gaussian-tail companding function, energy-efficiency model, constrained grid-search procedure, and matched comparison scripts were newly implemented for this study. No figures, raw numerical results, or simulation datasets from the earlier work were reused. Text describing common methodological foundations was rewritten and explicitly distinguished from new components in Table 1.

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Appendix

Table 8. Matched-Protocol comparison with AHO-PCG and component-wise ablation of CA-HPGC

Configuration	Expanded channel-state inputs	SRC/DCT/DHT hybrid mixing	Time-domain dominant-sample processing	Gaussian-tail companding	Energy-latency objective	PAPR at CCDF =10 ⁻³ (dB)	BER at 20 dB	EVM (%)	OOB power (dBm)	Energy per bit (μJ/bit)	Latency (ms/frame)
Conventional UPMC	No	No	No	No	No	10.70	1.1×10^{-3}	7.40	-27.20	0.84	0.74
AHO-PCG reimplementation	SNR/MCS only	No, discrete DFT/SRC/ZCT transform selection	No, frequency-domain SSC	No, logarithmic Gaussianized dynamic companding	No	8.40	8.2×10^{-4}	4.90	-36.00	0.72	1.55
A1: AHO-PCG + expanded channel state	Yes	No, discrete DFT/SRC/ZCT transform selection	No, frequency-domain SSC	No, logarithmic Gaussianized dynamic companding	No	8.00	7.1×10^{-4}	4.30	-37.80	0.68	1.60
A2: A1 + modified transform bank and hybrid mixing	Yes	Yes	No, frequency-domain SSC	No, logarithmic Gaussianized dynamic companding	No	7.40	5.8×10^{-4}	3.60	-39.80	0.61	1.68
A3: A2 + time-domain dominant-sample processing	Yes	Yes	Yes	No, logarithmic Gaussianized dynamic companding	No	6.90	4.6×10^{-4}	3.10	-41.50	0.55	1.74
A4: A3 + Gaussian-tail companding	Yes	Yes	Yes	Yes	No	6.65	3.8×10^{-4}	2.85	-42.60	0.51	1.78
Full CA-HPGC	Yes	Yes	Yes	Yes	Yes	6.50	3.4×10^{-4}	2.70	-43.30	0.49	1.82