

Efficient Temporal Feature Representations for RF Power Amplifier Behavioral Modeling Using Compact Temporal Convolutional Neural Networks

Emeli Krebs, Luiz Augusto Shoit Tsurukawa, Ali Mansour and Eduardo Gonçalves de Lima

Abstract—This paper investigates parameter-efficient temporal neural architectures for behavioral modeling of RF power amplifiers using physically meaningful feature representations. The investigated architectures were inspired by recent parameter-efficient temporal convolutional network digital predistortion (TCN-DPD) structures proposed in the literature. For complex signals, two temporal feature representations are compared: a Cartesian representation based on the real and imaginary signal components, and a physically motivated representation based on amplitude and phase-difference information using $a(n)$, $\cos(\Delta\theta(n))$, and $\sin(\Delta\theta(n))$. In addition, shared and feature-wise temporal convolutional strategies are investigated. The proposed feature-wise strategy is inspired by depthwise separable convolution concepts introduced in convolutional neural networks. Simulations with Wi-Fi 7 signals demonstrate that the proposed temporal representation consistently outperforms the direct Real/Imag (RI) representation. Best overall results achieved a normalized mean square error (NMSE) around -30 dB using shared TCNN convolutions. More importantly, compact feature-wise architectures revealed that the proposed representation maintained strong performance under severe parameter reduction, achieving about -28 dB using only 84 real-valued parameters, while the RI representation achieved around -22 dB under similar conditions. The obtained results indicate that physically meaningful temporal features significantly improve parameter efficiency in compact RF TCNN.

Keywords—RF behavioral modeling; Temporal Convolutional Neural Networks; Temporal feature representations.

I. INTRODUCTION

RF power amplifiers (PAs) operating close to saturation present nonlinear distortion and memory effects that degrade signal quality and spectral efficiency [1], [2]. These effects become increasingly important in modern wideband wireless communication systems employing high peak-to-average power ratio signals, such as Wi-Fi 7 and beyond-5G waveforms. Behavioral modeling and digital predistortion (DPD) techniques are commonly used to compensate nonlinear RF distortion [3], [4]. Classical approaches such as the Memory Polynomial (MP) and Generalized Memory Polynomial (GMP) models [3] provide good performance with relatively low complexity, but rely on predefined nonlinear basis functions; a direct comparison against these baselines is left for Section VII.

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Recently, neural-network-based approaches have attracted considerable attention for RF behavioral modeling and DPD applications [5]. In particular, Temporal Convolutional Neural Networks (TCNNs) have emerged as promising structures for parameter-efficient RF modeling due to their capability to extract temporal nonlinear patterns associated with memory effects.

Our study is inspired by the TCN-DPD architecture [6] and investigates the impact of temporal feature representations and feature-wise convolutional strategies for compact and interpretable RF behavioral modeling architectures. This work investigates the impact of physically motivated temporal features [7] on parameter efficiency and modeling accuracy in compact TCNN structures.

The proposed feature-wise temporal convolution strategy is conceptually related to depthwise separable convolution approaches introduced in convolutional neural networks [8]. However, the feature-wise processing is adapted to RF temporal behavioral modeling, where each temporal filter becomes associated with a physically meaningful RF feature.

The main contributions of this manuscript are as follows:

- comparison between Cartesian and Polar Coordinates;
- investigation of shared and feature-wise temporal convolutions;
- analysis of parameter efficiency in compact TCNN architectures;
- experimental validation using RFWebLab measurements with Wi-Fi 7 signals.

II. MEMORY POLYNOMIAL MODEL

The Memory Polynomial (MP) model [3] is widely adopted for classical RF behavioral models structures due to its relatively low computational complexity and good capability to represent nonlinear memory effects.

The MP model can be expressed as follows:

$$y(n) = \sum_{p=1}^P \sum_{m=0}^M h_{p,m} x(n-m) |x(n-m)|^{p-1}, \quad (1)$$

where $x(n)$ and $y(n)$ are the complex input and output baseband signals, P is the nonlinear order, M is the memory depth, $h_{p,m}$ are complex-valued coefficients, and $|x(n)|$ represents the amplitude (or envelope magnitude) of the complex sample $x(n)$.

Although the MP model provides good performance for many RF applications, its nonlinear basis functions remain

predefined. This motivates the investigation of neural structures capable of learning temporal nonlinear representations directly from measured data.

III. TEMPORAL FEATURE REPRESENTATIONS

Two temporal feature representations are investigated in this work. Let the complex baseband input signal be represented as

$$x(n) = I(n) + jQ(n) = a(n)e^{j\theta(n)}, \quad (2)$$

where $a(n) = |x(n)|$ and $\theta(n) = \angle x(n)$ is the signal phase.

A. Real/Imag Representation

The first representation uses the real and imaginary components directly:

$$\mathbf{u}_{RI}(n) = \begin{bmatrix} \Re\{x(n)\} \\ \Im\{x(n)\} \end{bmatrix}. \quad (3)$$

where $\Re\{x(n)\}$ and $\Im\{x(n)\}$ represent the real and imaginary components of the complex baseband signal $x(n)$, respectively. This representation lets the network learn the complex RF relationship directly in a Cartesian coordinate system.

B. Amplitude and Phase-Difference Representation

The second representation uses amplitude and phase-difference features:

$$\mathbf{u}_{PCS}(n) = \begin{bmatrix} a(n) \\ \cos(\Delta\theta(n)) \\ \sin(\Delta\theta(n)) \end{bmatrix}, \quad (4)$$

where

$$\Delta\theta(n) = \theta(n) - \theta(n-1). \quad (5)$$

The use of $\cos(\Delta\theta(n))$ and $\sin(\Delta\theta(n))$ instead of directly using $\Delta\theta(n)$ in radians avoids phase discontinuities caused by the $[-\pi, \pi]$ wrapping effect. This provides a continuous periodic representation of phase evolution, which is more suitable for temporal convolutional processing and neural network optimization.

The proposed temporal representation is physically motivated by the envelope and phase dynamics of RF signals. Since RF power amplifiers are strongly influenced by amplitude transitions and phase evolution, the use of amplitude and phase-difference features provides a more meaningful temporal representation than direct Cartesian-domain representations.

For each time instant, delayed versions of the features are organized into a $3 \times (M+1)$ temporal feature matrix:

$$\mathbf{U}(n) = [\mathbf{u}(n) \quad \mathbf{u}(n-1) \quad \cdots \quad \mathbf{u}(n-M)] \quad (6)$$

where each column corresponds to one delayed temporal sample.

IV. INVESTIGATED TCNN ARCHITECTURES

A. Shared TCNN

The proposed shared TCNN architecture, inspired by the parameter-efficient TCN-DPD structure [6], processes all temporal features jointly inside the convolutional stage.

While this architecture employs dilated temporal convolutions and residual blocks for digital predistortion, this study focuses on compact behavioral modeling structures and investigates how temporal feature representations affect parameter efficiency and modeling accuracy.

The shared structure is illustrated in Fig. 1.

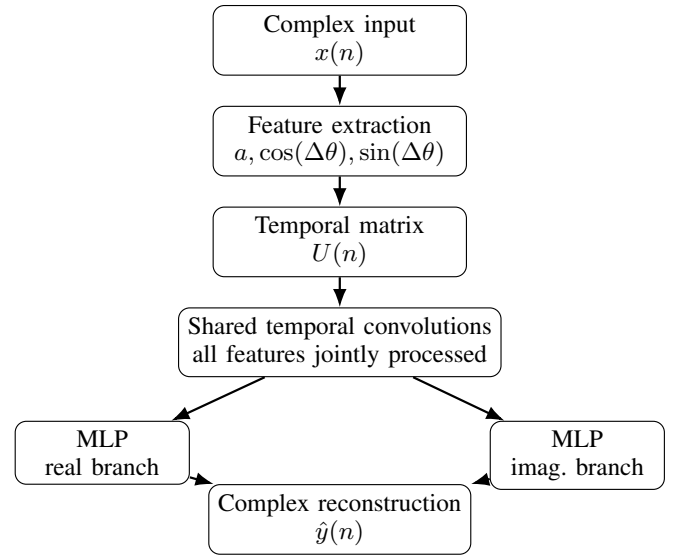


Fig. 1. Shared TCNN architecture. Temporal convolutions jointly process all temporal features. Multi-layer perceptron (MLP).

Since all features are jointly processed, the convolutional filters can learn interactions between amplitude dynamics, phase transitions, and memory effects.

Consequently, each temporal kernel may combine information from multiple physical quantities and temporal delays simultaneously.

B. Feature-Wise Separated TCNN

In the feature-wise separated architecture, shown in Fig. 2, each temporal feature is processed independently by its own temporal filter. This strategy is conceptually related to depth-wise separable convolutions introduced in [8], where each channel is processed independently before higher-level feature fusion. In addition, the real and imaginary output branches are modeled using fully separated networks. This structure considerably reduces the number of trainable parameters and increases interpretability, since each temporal filter becomes directly associated with a specific physical quantity, such as amplitude dynamics or phase-transition behavior.

Differently from shared convolutions, the feature-wise structure restricts direct interactions between distinct temporal features during the convolutional stage. Consequently, the quality of the temporal representation itself becomes more important.

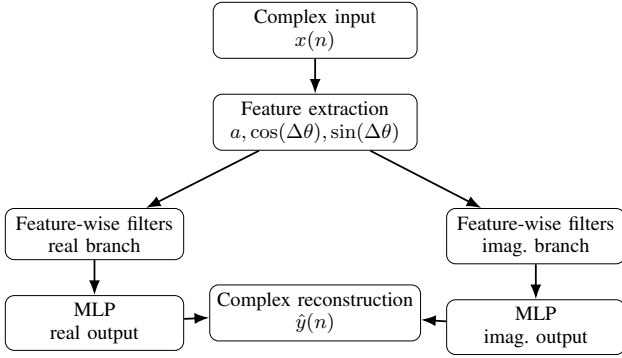


Fig. 2. Feature-wise separated TCNN architecture. Each temporal feature is independently processed before real and imaginary reconstruction.

V. TRAINING AND EXPERIMENTAL SETUP

The complex modeling error was separated into real and imaginary components:

$$\mathbf{e} = \begin{bmatrix} \Re\{y(n) - \hat{y}(n)\} \\ \Im\{y(n) - \hat{y}(n)\} \end{bmatrix}. \quad (7)$$

All trainable parameters (convolutional coefficients, weights, and biases) were concatenated into a single vector and estimated using nonlinear least-squares optimization (`lsqnonlin`). The input and output signals were normalized by their maximum absolute values to improve numerical stability during optimization.

The validation performance was evaluated using the normalized mean square error (NMSE):

$$\text{NMSE} = 10 \log_{10} \left(\frac{\sum_n |y(n) - \hat{y}(n)|^2}{\sum_n |y(n)|^2} \right). \quad (8)$$

The RF measurement dataset was obtained using the RFWebLab platform [9]. The source signal was based on IEEE 802.11be Wi-Fi 7 waveforms generated in Cadence Virtuoso using 256-QAM modulation with 20 MHz bandwidth and the input peak power adjusted to -12 dBm.

The RFWebLab setup implements a Gallium Nitride (GaN) power amplifier measurement platform. The employed test board was the Cree CGH40006-TB and the transistor was the Cree CGH40006P. The Power Amplifier (PA) presented approximately 50 dB gain.

After data acquisition, temporal synchronization between the input and output signals was performed using cross-correlation in order to compensate propagation and measurement delays.

The extraction and validation datasets were separated such that the maximum amplitude of the validation dataset remained below the maximum amplitude of the extraction dataset, avoiding extrapolation during validation.

The architectural hyperparameters (memory depth $M = 5$, $n_h = 10$ hidden neurons for the baseline models, and $F_1 = 3$, $F_2 = 4$ temporal filters per convolutional stage) were empirically selected after preliminary experiments, seeking a compromise between modeling accuracy, parameter efficiency, and optimization stability; larger configurations provided only

marginal accuracy gains while substantially increasing the parameter count. The compact feature-wise experiments reported below employed reduced hidden layer sizes ($n_h = 5$) in order to evaluate the impact of temporal feature representations under constrained parameter conditions.

VI. RESULTS AND DISCUSSION

A. Quantitative Comparison

Table I summarizes the validation NMSE and parameter count for the investigated architectures.

TABLE I
VALIDATION NMSE AND PARAMETER COUNT FOR THE INVESTIGATED TCNN STRUCTURES.

Model	Parameters	NMSE
Shared PCS-TCNN	234	-30.82 dB
Shared RI-TCNN	198	-27.43 dB
Feature-wise PCS, $n_h = 5$	84	-27.99 dB
Feature-wise RI, $n_h = 5$	62	-21.83 dB
Feature-wise RI, $n_h = 10$	110	-21.89 dB

The best overall result was obtained using the shared TCNN with the proposed amplitude and phase-difference (PCS) representation, achieving a validation NMSE of -30.82 dB, while the feature-wise experiments further revealed that physically meaningful temporal features become increasingly important as the model complexity decreases.

Using only 84 real-valued parameters and a reduced hidden layer size of $n_h = 5$, the feature-wise experiments indicate that the proposed temporal representation remains considerably more robust under compact architectural constraints than the direct RI representation.

Additionally, increasing the RI hidden layer size from $n_h = 5$ to $n_h = 10$ only improved the NMSE from -21.83 dB to -21.89 dB, despite the increase in parameter count from 62 to 110 parameters.

These results suggest that the proposed amplitude and phase-difference representation provides a significantly more efficient temporal description of RF nonlinear dynamics than direct Cartesian-domain representations.

B. AM-AM and AM-PM Characteristics

The estimated output accurately follows the measured amplitude modulation-to-amplitude modulation (AM-AM) characteristic, shown in Fig. 3, especially in medium and high amplitude regions where nonlinear compression becomes dominant. Slightly larger deviations appear at low amplitudes due to weaker nonlinear dynamics and measurement noise.

The proposed TCNN captures the dominant amplitude modulation-to-phase modulation (AM-PM) behavior introduced by the RF PA, see Fig. 4. The obtained results indicate that the proposed temporal representation efficiently encodes nonlinear phase dynamics associated with RF memory effects.

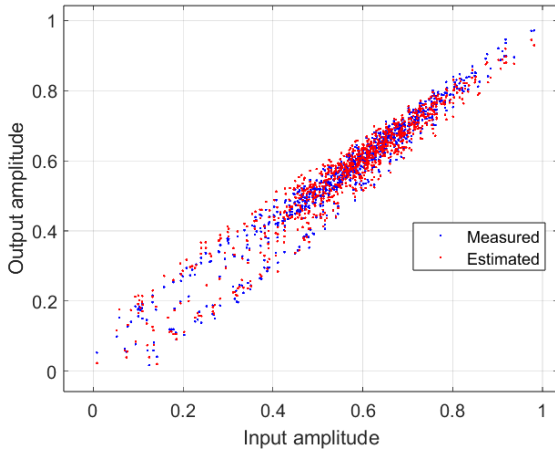


Fig. 3. AM-AM characteristic for the shared TCNN using the proposed temporal representation.

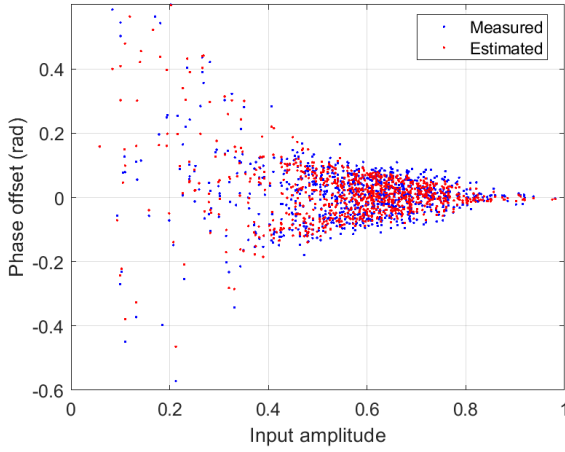


Fig. 4. AM-PM characteristic for the shared TCNN using the proposed temporal representation.

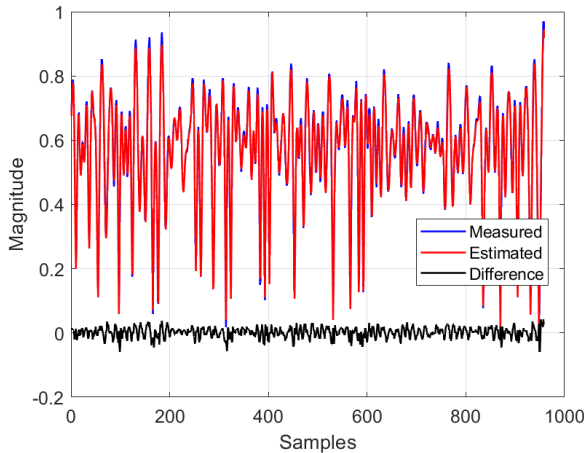


Fig. 5. Time-domain comparison between measured and estimated output envelopes.

C. Temporal Reconstruction

The reconstructed envelope, in Fig. 5, closely follows the measured output waveform over time, demonstrating that the

proposed temporal convolutions successfully capture nonlinear envelope memory dynamics and rapid amplitude transitions.

Fig. 6 presents the real and imaginary reconstructed components, side by side.

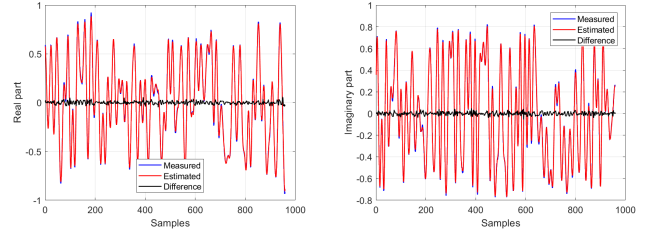


Fig. 6. Time-domain comparison between measured and estimated real (left) and imaginary (right) components.

The close agreement between measured and estimated real and imaginary components demonstrates that the proposed architecture reconstructs not only the signal envelope, but also the complex baseband waveform structure associated with nonlinear RF behavior.

D. Error and Spectral Analysis

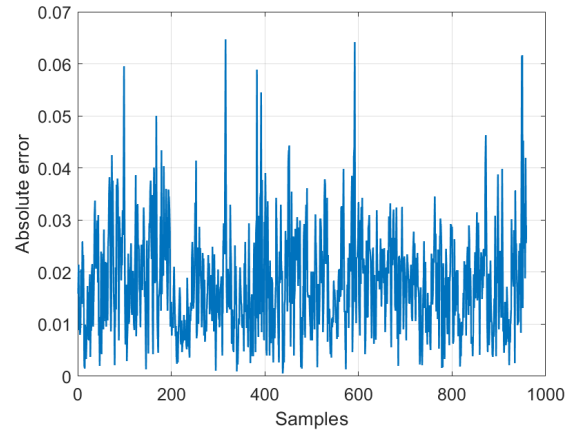


Fig. 7. Absolute modeling error for the shared TCNN using the proposed temporal representation.

The modeling error shown in Fig. 7 remains relatively low for most temporal samples, with localized peaks mainly concentrated around abrupt envelope transitions and low-amplitude regions. These regions are typically more difficult to model due to weaker signal energy and stronger sensitivity to nonlinear memory fluctuations.

The estimated signal accurately reconstructs the dominant in-band spectral behavior of the RF PA output, see Fig. 8. The obtained spectrum demonstrates very good agreement between measured and estimated signals, particularly around the main spectral components and adjacent frequency regions.

Small discrepancies remain in out-of-band regions, where weak spectral regrowth components become more difficult to model using compact architectures with reduced parameter count.

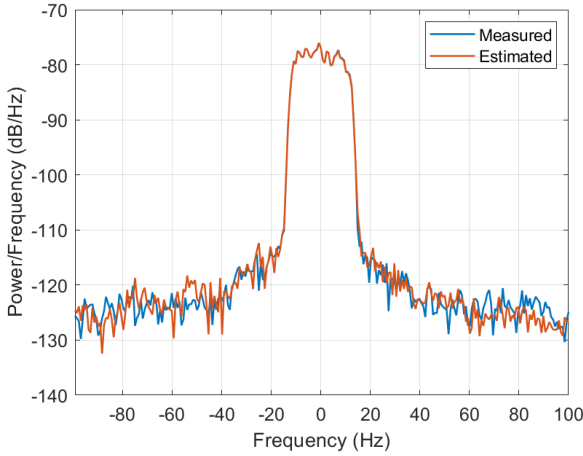


Fig. 8. Power Spectral Density (PSD) comparison between measured and estimated output signals.

E. Discussion on Parameter Efficiency

Our simulations corroborate that temporal feature representation plays a central role in compact RF behavioral modeling architectures. While larger shared TCNN structures achieve the best overall NMSE, the feature-wise experiments reveal a more important result: physically meaningful temporal features become increasingly relevant as the model complexity decreases. The proposed PCS representation maintains strong modeling capability even with highly compact structures, whereas the direct RI representation suffers severe degradation under reduced parameter conditions.

This is evident in Table I, where doubling the RI hidden layer size improves the NMSE by a negligible 0.06 dB despite doubling the parameters. This saturation suggests that the limiting factor is not network capacity, but the geometric inefficiency of implicitly uncoupling AM-AM/AM-PM dynamics from Cartesian coordinates; explicit u_{PCS} features bypass this overhead, maximizing parameter efficiency.

Intuitively, the RI representation forces the network to implicitly recover magnitude- and phase-related quantities from nonlinear combinations of $I(n)$ and $Q(n)$ before approximating the amplifier's AM-AM/AM-PM response, spending part of its limited capacity on this coordinate transformation. Since $u_{PCS}(n)$ already supplies $a(n)$, $\cos(\Delta\theta(n))$, and $\sin(\Delta\theta(n))$ directly, even a handful of parameters can be dedicated entirely to memory and nonlinearity, explaining the disproportionate robustness of the feature-wise PCS model under severe compression.

Therefore, the main contribution of this work is not only the improvement in NMSE performance, but also the demonstration that physically meaningful temporal representations can substantially improve parameter efficiency in RF temporal convolutional neural networks.

VII. CONCLUSION

This work investigated efficient temporal feature representations for compact RF temporal convolutional neural networks. The results demonstrated that the proposed amplitude and

phase-difference representation consistently outperformed the widely used Real/Imag representation, with the best overall performance obtained using shared TCNN convolutions combined with this representation.

More importantly, the compact feature-wise architectures demonstrated that physically meaningful temporal representations substantially improve parameter efficiency compared to direct RI representations. It is worth noting that the phase information discarded in the PCS feature extraction (Section III) is not lost: the complex reconstruction stage reintroduces the instantaneous input phase $\theta_x(n)$ before producing $\hat{y}(n)$, so the mapping from $u_{PCS}(n)$ back to the complex output remains well defined. This reconstruction, however, relies on the input phase rather than an independently estimated output phase, which is adequate for behavioral modeling but would require further scrutiny for DPD: an eventual predistorter built on this representation would need to verify that the learned mapping $s(n) \mapsto \tilde{s}(n)$ remains locally invertible (e.g., via its Jacobian) across the amplifier's operating range. A systematic analysis of this reconstruction step in closed-loop DPD scenarios is left for future work.

The present comparison is restricted to a single GaN PA, a single Wi-Fi 7 configuration, and the NMSE metric. Benchmarking against classical MP/GMP baselines, evaluating ACLR/EVM, and assessing generalization across amplifiers and signal types are important next steps, together with a complete DPD+PA cascade evaluation.

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