Experimental Demonstration of a Machine Learning-Based Piece-Wise Digital Predistortion Method in 5G NR Systems

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- Power amplifier (PA) is a non-linear (NL) dynamic system and can be modeled as a Volterra system.

- In practice, pruned Volterra models such as generalized memory polynomial (GMP) are commonly used.

- PA Modeling with a single Volterra model is often difficult.

- Piece-wise (PW) modeling approach is an effective alternative.

- The GMP model with NL polynomial degree P and memory depth of K for the leading and lagging memories as GMP (P,K).
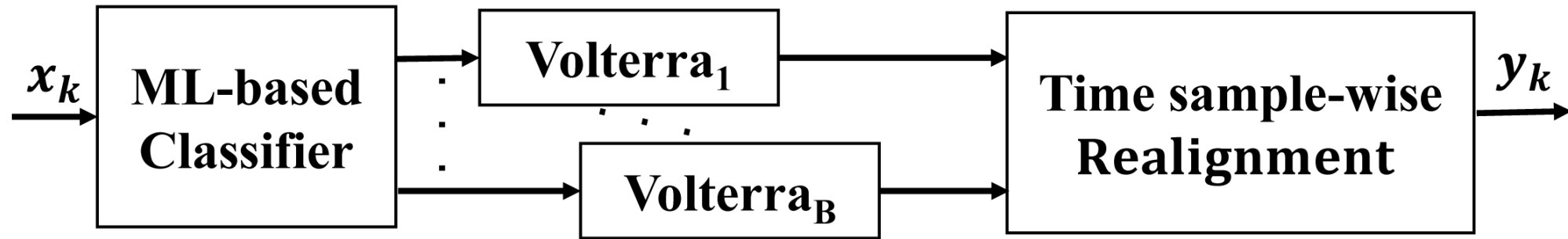
Fig 1. Block diagram of the proposed scheme.

- The input signal envelope is fitted to a Rayleigh distribution for extracting the statistical parameters for feature construction.

- A machine learning (ML) classifier partitions the input signal into B classes and is then modeled by tailored Volterra models.

- Finally, the pre-distorted samples are re-aligned in time and sent to real PA.

- ML classifier features are constructed from signal statistics and the PA operating point.

- Following features are constructed:
  - $(|x_k| - \hat{\mu})^2$ *(i.e., square of deviation of the sample's amplitude from mean)*
  - $|x_k|^2$ *(i.e., sample's energy)*
  - $\mathrm{Re}(x_k)$ *(i.e., real part of the sample)*
  - $\mathrm{Im}(x_k)$ *(i.e., imaginary part of the sample)*
  - $|x_k|^2 - (v_{3\,\mathrm{dB}})^2$ *(i.e., deviation of the sample's energy from the 3 dB PA compression point)*
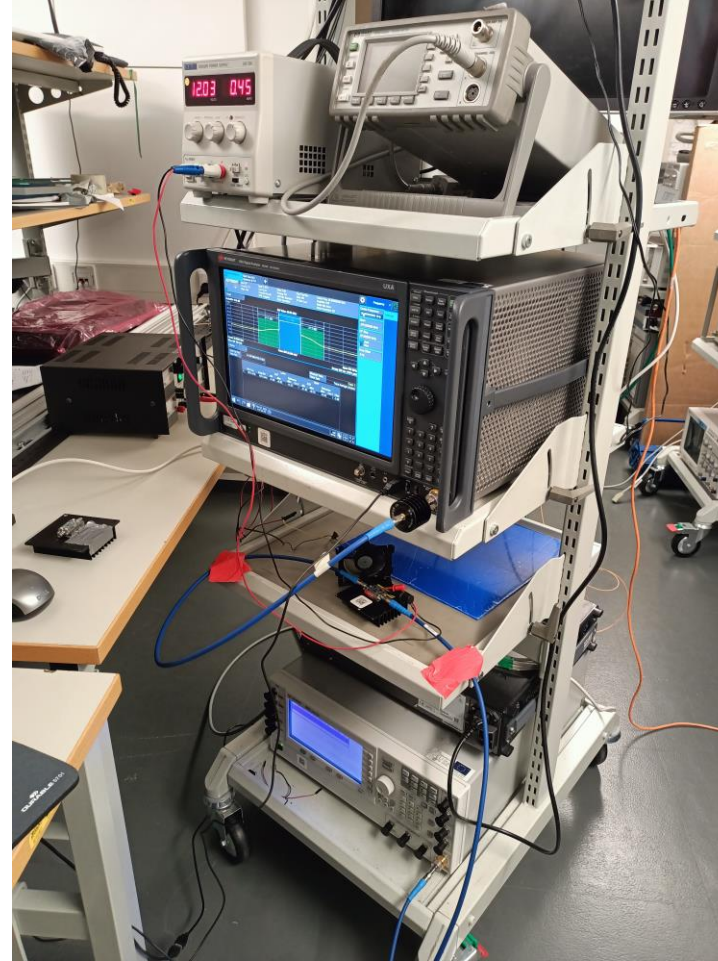
- These features can be computed with meager complexity.

Measurement Setup

Fig 2. Photograph of the measurement setup.

- **Device under test (DUT):**
  Caio CA2630-141

- **Operating frequency:** 28 GHz

- **Data:** 64-QAM 5G NR signal (100 MHz bandwidth)

- **PAPR information:** CCDF of PAPR with 8.9 dB at 0.1 probability and 10.9 dB at 0.001 probability.
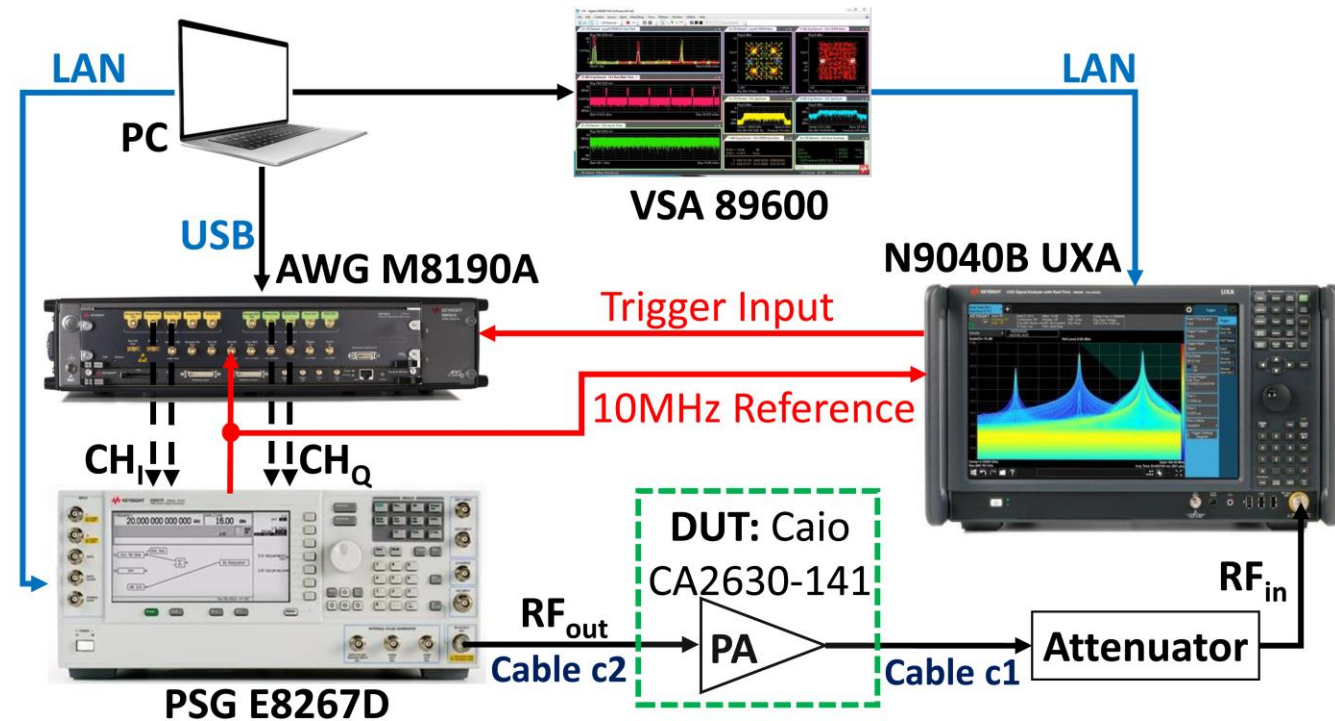

Fig 3. Re-illustration of the measurement setup.

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ML Classifier Model

- Two ML methods namely k-nearest neighbors (kNN) with **10** neighbors and decision tree (DT) were considered.

- The collected dataset has $\mathbf{0.775 \times 10^6}$ samples and $\mathbf{10\%}$ of the dataset is used for training.

- The classifier models with less than 5 features have shown sub-optimal performance.

- Table 1 indicates that statistical feature selection favors less ML algorithmic complexity with reliable classification accuracies.

Sample Classes	kNN F_1 score	DT F_1 score
Class 1	0.94	0.97
Class 2	0.99	1
Class 3	0.99	1
Class 4	0.96	0.98
Class 5	0.92	0.96

Table 1. F1-scores over the test dataset for the two ML classifier models.
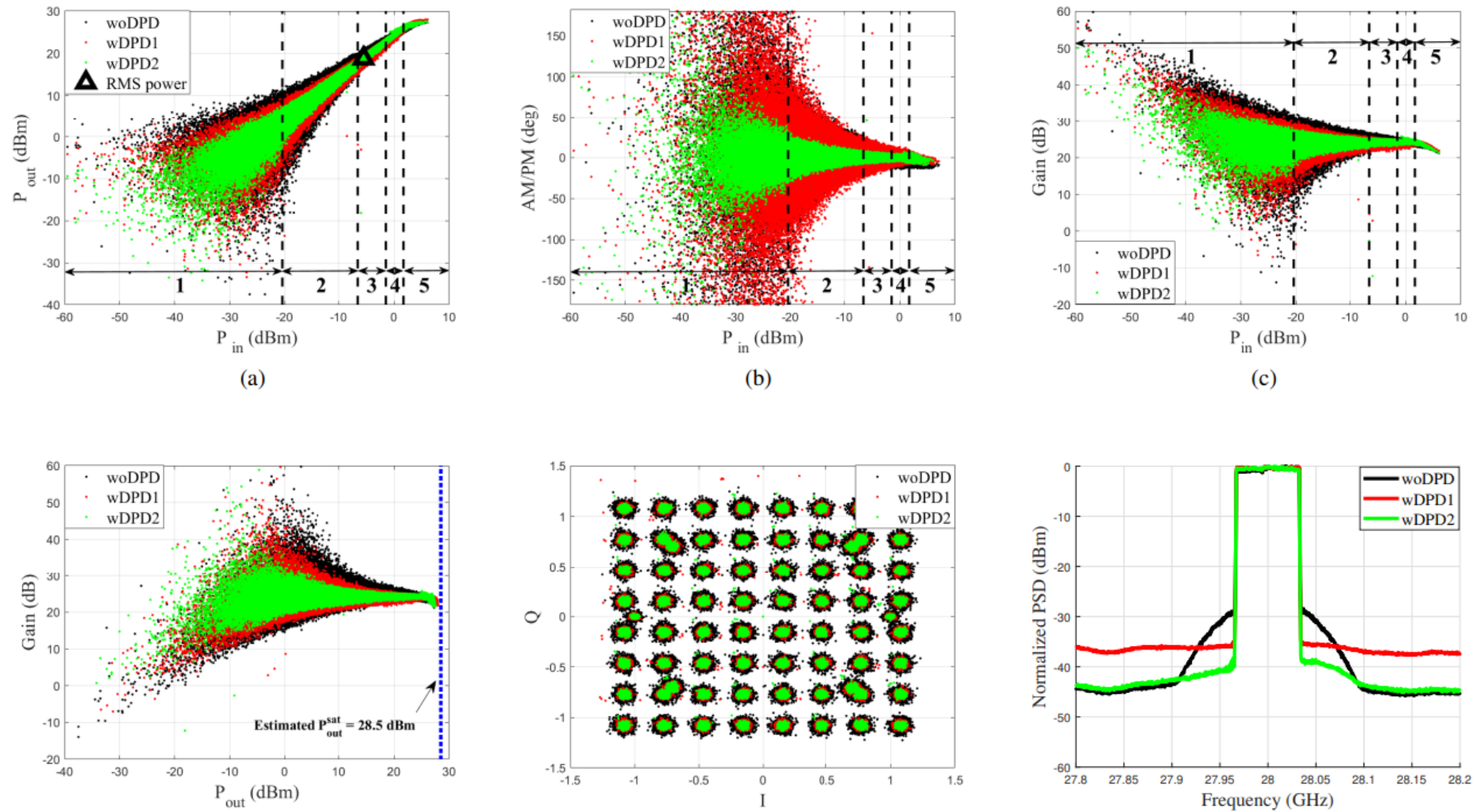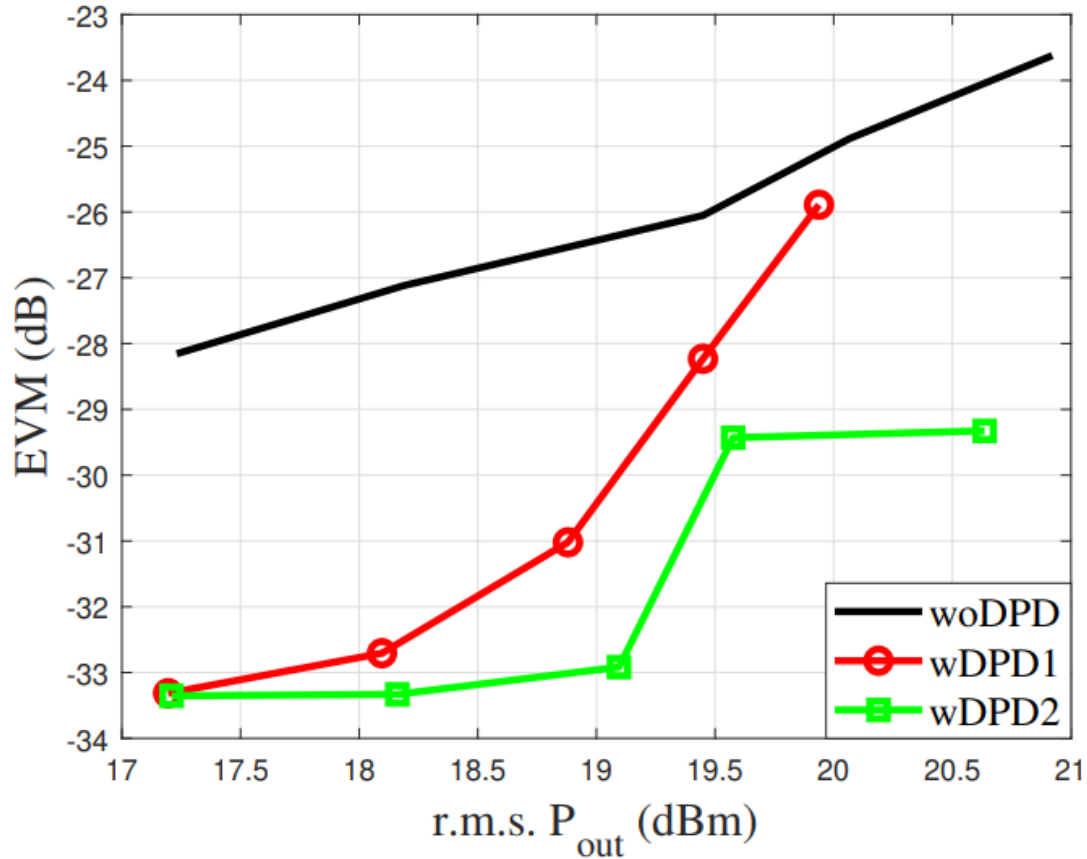
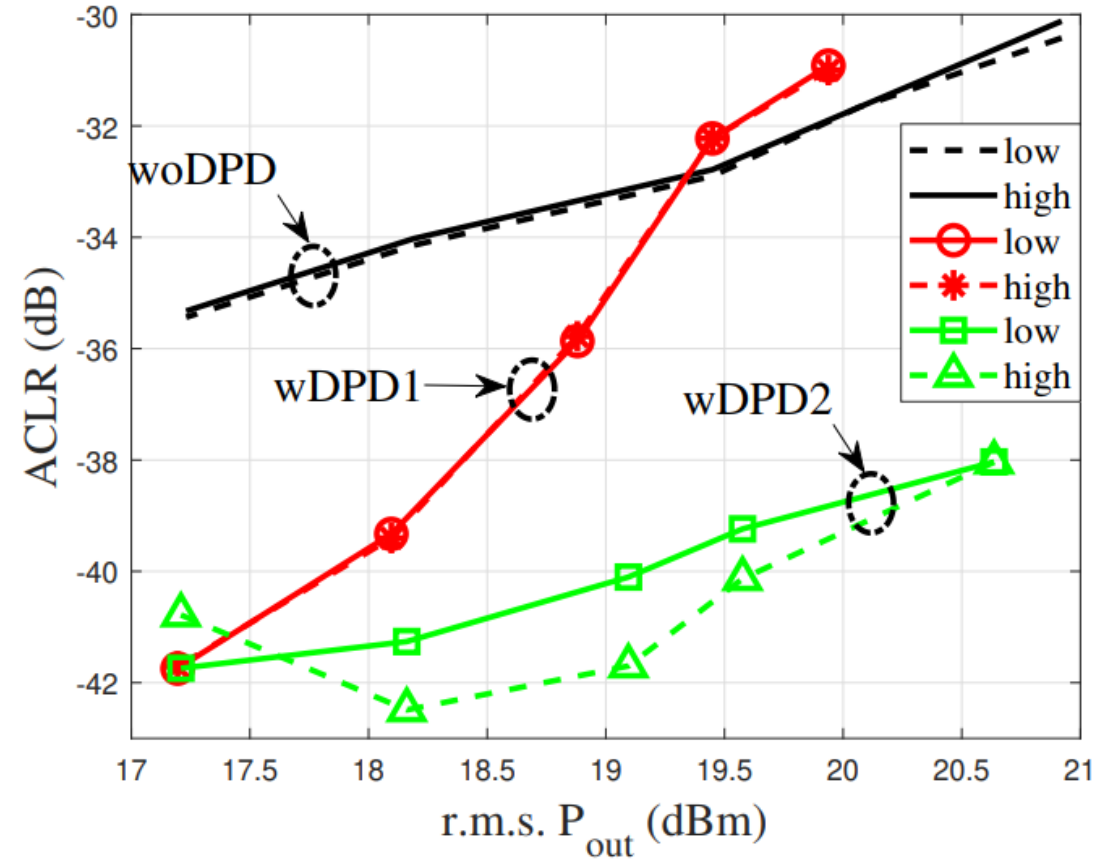<Session - Paper#>

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Fig 4. PA Linearization performance at r.m.s. $P_{in} = -5.5\ dBm$.

Fig 5. PA Linearization performance at different measured r.m.s. P_{in}.

- **The conventional single GMP and the proposed schemes require storage of 48 and 113 coefficients, respectively.**

- **The proposed scheme offers 69.68% and 70.72% complexity reduction in terms of complex multiplications and additions as shown in the Table .**

The DPD Method	Sample Class	GMP (P, K)	Number of coefficients Λ	% of total samples, i.e. $\frac{card(\kappa_i)}{card(\mathcal{N})}$	Total Multiplications	Total Additions
DPD1	-	$(5, 4)$	68	-	100.46×10^6	103.91×10^6
DPD2	1	$(2, 3)$	12	3.17 %	31.97×10^6	30.42×10^6
	2	$(3, 3)$	21	51.21 %		
	3	$(3, 3)$	21	37.70 %		
	4	$(3, 3)$	21	7.38 %		
	5	$(1, 1)$	1	0.5 %		

Table 2. Complexity comparison of single GMP method with the proposed scheme.

- A **low complex** ML-aided PW modeling for DPD is proposed.

- ML classifier features are constructed to the **input data's statistics** and the **selected PA operating point**.

- Statistical feature extraction additionally favors **less ML algorithmic complexity** with **reliable classification accuracies**.

- The experimental results indicate the proposed method is **promising** with a **good performance/complexity** trade-off than the conventional single GMP model.