Machine-Learning Based Digital Doherty Power Amplifier

Ma, R.; Benosman, M.; Manjunatha, K.; Komatsuszaki, Y.; Shinjo, S.; Teo, K.H.; Orlik, P.V.

TR2018-114 August 17, 2018

Abstract

This paper reports a new architecture of power amplifiers (PA), for which machine learning is applied in real-time to adaptively optimize PA performance. For varying input stimuli such as carrier frequency, bandwidth and power level, developed algorithms can intelligently optimize parameters including bias voltages, input signal phases and power splitting ratios based on a user-defined cost function. Our demonstrator of a wideband GaN Digital Doherty PA achieves significant performance enhancement from 3.0-3.8 GHz, in particular, at high back-off power with approximately 3dB more Gain and 20% higher efficiency compared with analog counterpart. To the authors best knowledge, this is the first reported work of model-free machine learning applied for Doherty PA control. It explores a new area of RF PA optimization, in which accurate analytical models and tedious manual tuning can be avoided.

IEEE International Symposium on Radio Frequency Integration Technology (RFIT)

Machine-Learning Based Digital Doherty Power Amplifier

(Invited Paper)

Rui Ma[1], Mouhacine Benosman[1], Koushik Manjunatha[1, 2], Yuji Komatsuzaki[3], Shintaro Shinjo[3]
Koon Hoo Teo[1], and Philip V. Orlik[1]

[1] Mitsubishi Electric Research Laboratories (MERL), Cambridge, MA 02139, USA, rma@merl.com
[2] University of Alabama, Tuscaloosa, AL 35487, USA
[3] Mitsubishi Electric Corporation, Information Technology R&D Center, Kamakura 247-8501, Japan

***Abstract*—This paper reports a new architecture of power amplifiers (PA), for which machine learning is applied in real-time to adaptively optimize PA performance. For varying input stimuli such as carrier frequency, bandwidth and power level, developed algorithms can intelligently optimize parameters including bias voltages, input signal phases and power splitting ratios based on a user-defined cost function. Our demonstrator of a wideband GaN Digital Doherty PA achieves significant performance enhancement from 3.0-3.8 GHz, in particular, at high back-off power with approximately 3dB more Gain and 20% higher efficiency compared with analog counterpart. To the authors' best knowledge, this is the first reported work of model-free machine learning applied for Doherty PA control. It explores a new area of RF PA optimization, in which accurate analytical models and tedious manual tuning can be avoided.**

***Index Terms*—Machine learning, Digital Doherty, GaN, Power Amplifier, Optimization**

I. INTRODUCTION

Recently, Digital Doherty PA (DDPA) development has made rapid progress and shown unique advantages compared with conventional analog Doherty PA [1-3]. Instead of using analog power divider (i.e. Wilkinson divider) to split RF input power for main and peaking amplifiers, multi input ports are independently fed and controlled in DDPA. It offers notable merits such as reduction of unnecessary power loss, when peaking amplifier is OFF at low power. Thus, it can obtain higher power gain compared with that of Analog DPA. More importantly, it also enables dynamic phase alignment, which is a key factor for DPA power efficiency, and linearity.

Nonetheless, in practice it is a tedious and experience-based procedure to obtain the optimum operating status for such a complex circuitry with multi-input architecture. This is because of the interaction among the multiple amplifiers, that active load modulation is occurring between main and peaking amplifiers output. In addition, both main and peaking PA require separate stimulus and bias voltage setting. For instance, optimum input signal's phase for main and peaking amplifier depends on input power levels, frequencies, signal modulations, bias voltages, and temperature. Altogether, these result in quite large space of variables. Thereby, brute force search of optimum control parameter becomes inefficient and can be hardly implemented in practice.

So far, the published papers are mainly relying on analytical model to create a static phase, input power and/or frequency mappings [2]. This has several limitations: (1) derived mathematical equations only providing approximation of highly non-linear relationship within PA (i.e. *arctan* function); (2) bias voltages optimization not included so far (3) Open-loop implementation without capturing the device-to-device variation or condition changes (i.e. ambient temperature). Manual tuning is still required to account for the dynamics of real systems and condition varies.

In this work, we proposed and validated a new machine-learning based optimization platform as shown in Fig. 1. In real-time, it adaptively controls and optimizes the operation of multi-input PA for dynamic stimuli and operating conditions. A dual-input Digital Doherty PA is chosen as a demonstrator, whose operation is optimized by AI (artificial intelligence) algorithms without any manual interaction.

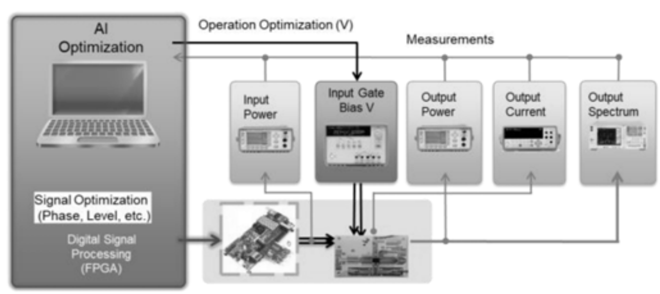
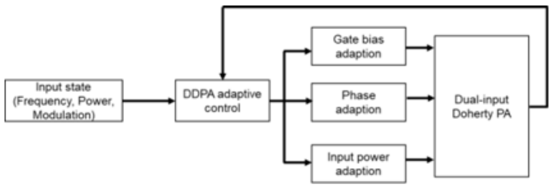


Fig. 1. System diagram of proposed real-time closed loop machine learning based dual-input digital Doherty PA.

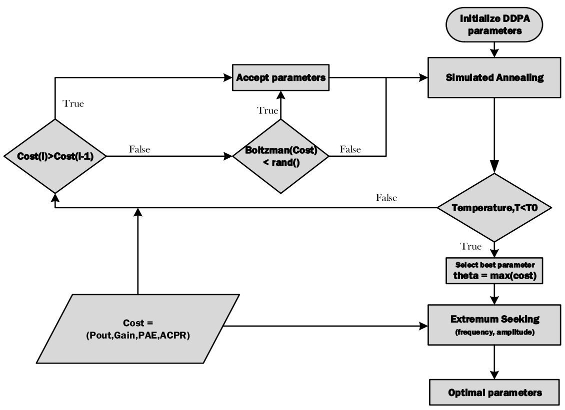
This paper is organized as follows: Section II explains the optimization algorithms, and Section III presents measurement results. Conclusion and future works are given in Section IV.

II. Algorithm

The architecture of, and machine learning algorithm for dual input digital Doherty amplifier in this work are shown in Fig. 2.



(a)



(b)

Fig. 2. (a) Topology of adaptively controlled DDPA, and (b) machine-learning algorithm flow chart used in DDPA.

Key parameters including gate bias voltages for main amplifier (*Vg_main*) and peaking amplifier (*Vg_peak*), dual-input signal's relative phase ($\Delta\Phi$), and power ratio (α) are adaptively optimized by algorithm. It performs the optimization in an iteratively manner based on the measured PA output performance. A cost function is defined to evaluate PA performance including output power, linearity (ACPR: adjacent channel power ratio), Gain with proper weighting factor depending on the applications. To search for the optimal control parameters θ^* with maximum cost function $Q(\theta)$:

$$\theta^* = \underset{\theta \in U}{\operatorname{argmax}} \, \mathrm{Q}(\theta)$$

where θ is a vector of the amplifier tuning parameters defined as $\theta = [Vg\_main,\ Vg\_peak,\ \Delta\Phi,\ \alpha]$. We implemented model-free optimization methods of simulated annealing (SA) and extremum seeking (ES), as shown in Fig.2 (b). The combination of SA and ES makes the system hybrid, where SA captures the random and abrupt variation in the system mainly due to frequency and input power level variations, whereas ES captures slow variation in the model due to temperature.

There are two phases to find the optimum solution of θ^*

- **Phase I (SA):**

Starting with a random initial point θ_0 and Temperature T. For each iteration randomly generate θ within the pre-defined boundary while decreasing the temperature T with a discount factor γ as $T \leftarrow \gamma * T$.

For each random move at i^{th} iteration, determine the cost $Q(\theta,t)$, and accept the move and store θ if

$$Q(\theta,t)-Q(\theta,t-1)>0$$

In case if the condition is not met, then by using Boltzmann condition, the random move can be accepted as follows,

$$rand[0,1] < e^{\wedge}((-(Q(\theta,t)-Q(\theta,t-1))/T))$$

If the above conditions are not met, then that particular move is not accepted and the next random point is generated. We accept some random moves even though their cost is less than the previous cost to avoid local minimums. The above procedure repeated until the Temperature T is above the threshold T_0.

Next, the best θ_best with the maximum cost $Q(\theta)$ is selected to find the best optimal parameters to achieve maximum cost within the explored set of values. Exploitation phase ensures to find the global optimum.

- **Phase II (ES):**

Algorithm then switches to ES once DDPA achieves maximum cost within the explored set of values. The goal of ES phase is to fine tune the values of optimal parameters with a local search. The extremum seeking iteratively perturbs the parameter of the amplifier with a perturbation signal having a predetermined frequency until a termination condition is met [5].

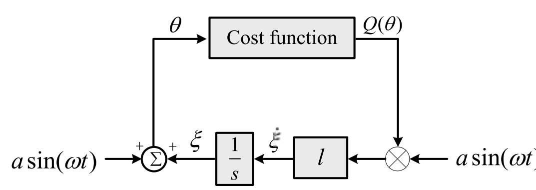


Fig. 3. Schematic of ES controller for the simple case of one tuning parameter.

Fig. 3 illustrate the basic concept of ES algorithm for the case of one tuning parameter. The ES controller injects a sinusoidal perturbation $asin(\omega t)$ into the system, resulting in an output of the cost function. This output is subsequently multiplied by $asin(\omega t)$. The resulting signal after multiplying a gain l, an estimate of the gradient of the cost function with respect to the cost function θ. The gradient estimate is then passed through an integrator 1/s and added to the modulation signal $asin\omega t$.

III. EXPERIMENT

A test bench is built for demonstrator testing with a Dual-channel digital GaN Doherty amplifier.

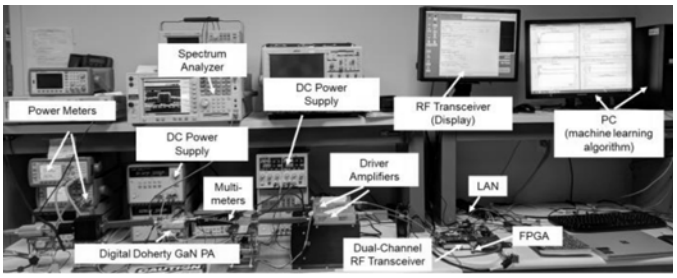


Fig. 4. Measurement setup of machine-learning DDPA.

We implemented the optimization algorithems in Matlab running on Windows PC. The automatic testbench including Spectrum analzyer (Agilent E4440A), power meter (Agilent N1912A), DC power supply (Agilent E3634A) of gate bias voltages control are connected to Windows PC via ethernet. AD9371 dual-channel RF transciver and Xilinx FPGA ZC706 are used to provide input RF signals with driver amplifiers from MiniCircuits (ZHL-16W-43+). The reported wideband GaN Doherty PA is modified at the input for DDPA topology [5].

It should be mentioned that our machine learning algorithm is different from the type of deep learning such as DNN (deep neural network) in the sense that it neither require massive training data nor powerful computation capability.

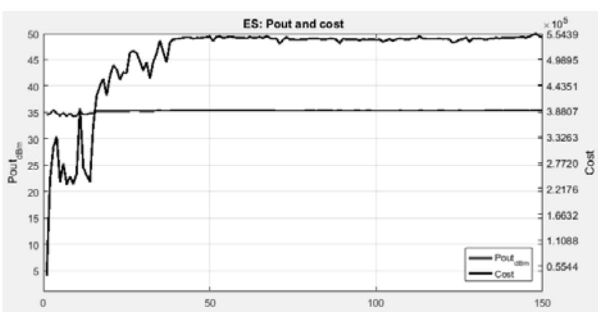
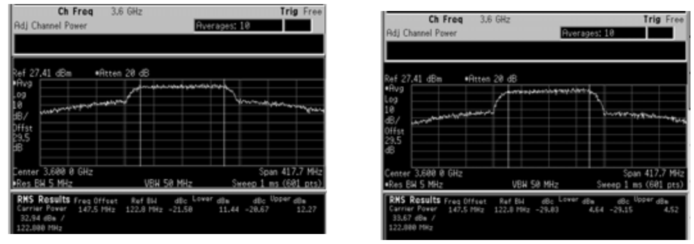


Fig. 5. Measured output power and cost function with adaptation of optimization algorithm.

Fig. 5 shows the iterative procedure of improving output power (P_{out}) and cost function. It takes about 40 iterations for SA to perform random exploration with fast convergence. It is then followed by ES algorithm for fine tuning to account for effects such as temperature changes.

Fig. 6. shows the linearity also improves after iteration by 10dB for 150MHz instannece signal stimuls at 3.6GHz carrier frequency without any digital predistortion. Fig. 7 shows more than 20% efficiency for AI-DPA compared with analog DPA (same output matching) for CW signal at 3.6GHz with power sweep.



(a) (b)

Fig. 6. ACPR comparison before (a) and after optimization.

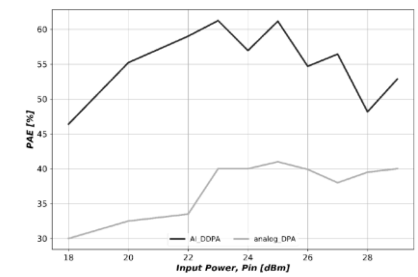


Fig. 7. PAE comparison between AI-DPA and analog DPA.

IV. CONCLUSION

We proposed and experimentally valiated a new model-free self-adptive optimzation method for RF power amplifier. The built prototype shows significant performance improvement comparied the analog version with promising potential to be applied to advaned RF circuit optimzation.

REFERENCES

[1] R. Ma, K. Teo, S. Shinjo, K. Yamanaka and P. M. Asbeck, “A GaN PA for 4G LTE-Advanced and 5G,” *IEEE Microw. Mag.*, vol. 18, no. 7, pp. 77–85, Nov.-Dec. 2017.

[2] R. Darraji, P. Mousavi, and F. Ghannouchi, “Doherty Goes Digital: Digitally Enhanced Doherty Power Amplifiers,” *IEEE Microw. Mag.*, vol. 17, no. 8, pp. 41–51, Aug. 2016.

[3] S. Niu, K. A. Manjunatah, R. Ma, K. Teo, S. Shinjo, and Y. Komatsuzaki, “Stochastically approximated multiobjective optimization of dual input digital Doherty power amplifier,” *IEEE 10th International Workshop on Computational Intelligence and Application Symposium (IWCIA),* pp. 147-152, Hiroshima, Japan, Nov. 2017

[4] M. Benosman, “Learning-Based Adaptive Control: An Extremum Seeking Approach – Theory and Applications,” Butterworth - Heinemann Books, Aug. 2016.

[5] Y. Komatsuzaki, K. Nakatani, S. Shinjo, S. Miwa, R. Ma, and K. Yamanaka, “3.0-3.6 GHz Wideband, over 46% Average Efficiency GaN Doherty Power Amplifier with Frequency Dependency Compensating Circuits,” *IEEE Proc. of Topical Conference on RF/Microwave Power Amplifiers for Radio and Wireless Applications (PAWR),* pp.22-24, Phoenix, AZ, Jan. 2017.