Modeling of Long Term Memory Effects in RF Power Amplifiers with Dynamic Parameters

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***Abstract*—This paper presents a new radio frequency power amplifier behavioral model that is capable of modeling long term memory effects. The proposed model is derived by assuming linear dependence of the parameters of a conventional model to a long term memory parameter, which enables the model to better track the signal-induced changes of the power amplifier electrical behavior. The model is experimentally tested on a 100 W Doherty power amplifier, with a signal that has a step-like change in power, representative of a realistic communication system with bursty behavior. Results show that the proposed model is able to improve the normalized mean squared error performance by around 2–3 dB.**

I. Introduction

The main propelling factor in the relatively short history of radio frequency power amplifier (PA) behavioral modeling has been the need for efficient low complex algorithms that are able to properly describe PAs for given input signal characteristics. Communication signals in early generation mobile systems had relatively constant amplitude, which allowed system designers to utilize memoryless models. These systems were mainly designed for voice calls, and power amplifiers would routinely operate under steady-state temperature conditions.

As users demand for more services and higher data–rates increases, efficient spectral utilization became necessary and envelope varying communication signals have been employed. For these type of wideband and high peak to average signals, it is noticed that memory effects in the power amplifier become more pronounced. The output of a power amplifier not only depends on the current input sample, but on previous samples as well [1].

In [2] it was noted that there are mainly two categories of memory effects that degrade communication signals, electrical memory effects and electrothermal. The former is attributed to matching effects at the terminal impedances over the input signal, and the latter to temperature drifts, biasing effects and self heating which causes undesired effects on gain variations and PA behavior [3]. In [4], it was shown that for communication signals with wide modulation bandwidth, the electrical short term memory dominated the behavioral modeling performance.

As new communications signals and usage pattern emerge, modeling longer term memory effects are once again gaining in importance. In [4] and [5], thermal networks are developed to compensate for thermal gain variations. In [6] two tone measurements are used to identify long term memory effects and a new modeling equation is proposed. In [7], a circuit-based approach was used to construct a new model structure to include long-term memory effects with regards to the thermal filter of the PA.

In all these works, the focus has been on identifying and developing model structures that can model long term memory effects. In this work, we instead focus on deriving a model with parameters that depend on the long term memory effect. This enables us to extend most of the commonly derived behavioral models for PAs to include long term memory estimates with relatively low complexity.

II. Model description

A. Model formulation

Traditional PA behavioral models - which are linear in terms of parameters - can be written as

$$\mathbf{y} = \mathbf{H_x}\theta, \tag{1}$$

where $\mathbf{y}$ is a vector of the baseband output samples of the PA, $\mathbf{H_x}$ is a matrix consisting of column vectors of different nonlinear and memory of the baseband input signal $\mathbf{x}$, and θ are the model parameters vector. Different behavioral models solely differ in the proposed $\mathbf{H_x}$. Volterra based models like the memory polynomial model [8], generalized memory polynomial model [9] and others [1] belong to this group.

In the model we propose here, instead of developing a new $\mathbf{H_x}$ we focus on including the long term effects in the parameters of the behavioral model θ. The new behavioral model can thus be written as

$$\mathbf{y} = \mathbf{H_x}\theta(\mathbf{s}), \tag{2}$$

where $\theta(\mathbf{s})$ are the parameters of the behavioral model that depend on the long term memory estimate $\mathbf{s}$. Intuitively, this corresponds to an amplifier whose physical parameters may vary with the input signal, due to e.g. self-heating, biasing effects and etc. Assuming a simple first order dependence of the parameters with the long term behavior $\mathbf{s}$, the new proposed model can be written as

$$y_{\mathrm{LT}}[n] = \mathbf{H}_{x[n]}\left(\theta_0 + s[n]\theta_1\right), \tag{3}$$

where θ_0 are the commonly modeled static parameters of the behavioral model (static with respect to the long term memory term), and θ_1 are the dynamic parameters. $\mathbf{H}_{x[n]}$ are the columns of any RF behavioral model structure linear with parameters, for example the MP or Volterra models.

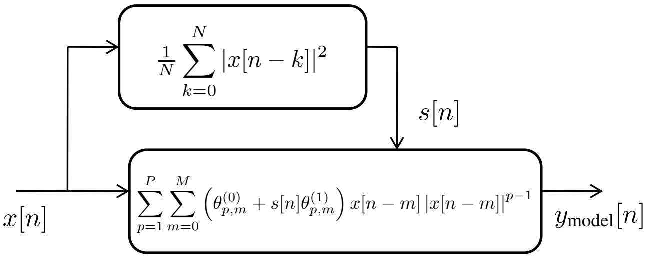

Fig. 1. Block diagram of the proposed model, with an MP model structure.

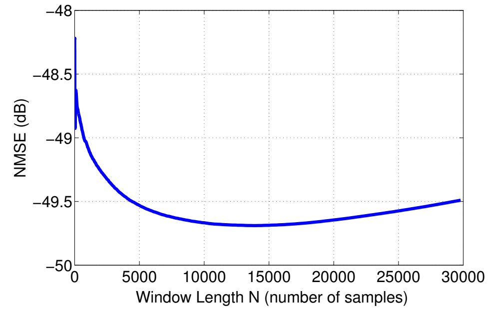

Fig. 2. Identification of window size, N, for the proposed behavioral model.

In order to be able to include long term memory effects without going to very high model order – which is to be avoided for both identification and run-time complexity reasons – or by pruning – which may not be an ideal solution – an estimate of the long term state variable has to be created. Since in this work it is assumed that changes in these long term effects are relatively slow (the power does not switch between high and low quickly), the average input power over a finite window is used as a metric for modeling the long term memory changes.

$$s[n] = \frac{1}{N}\sum_{k=n-N+1}^{n}|x[k]|^2 \tag{4}$$

N is the size of the window of the finite impulse response estimate. The larger the window size, the more the instantaneous power will be averaged. The block diagram for this model with an MP model structure is shown in Fig. 1.

B. Model Identification

In order to identify the parameters of this model, it can be noticed that once $s[n]$ is calculated from (4), with some re-writing of terms, equation (3) can be rewritten as

$$\mathbf{y}_{\text{LT}} = [\mathbf{H_x}\ \mathbf{SH_x}][\theta_0\ \theta_1]^T, \tag{5}$$

where $\mathbf{H_x}$ is any of the commonly proposed behavioral models in the literature, and $\mathbf{S}$ is the diagonal matrix of the column vector $\mathbf{s}$.

It can be noticed that with a known $s[n]$, the model is linear with respect to the parameters θ. Therefore the unknown parameters $[\theta_0\ \theta_1]^T$ can be calculated with normal least squares technique and written as

$$[\hat{\theta}_0\ \hat{\theta}_1]^T = \left([\mathbf{H_x}\ \mathbf{SH_x}]^T[\mathbf{H_x}\ \mathbf{SH_x}]\right)^{-1}[\mathbf{H_x}\ \mathbf{SH_x}]^T\mathbf{y}. \tag{6}$$

From equation (4), for the identification of $s[n]$, it can be noticed that the only unknown coefficient is N, the size of the window used to calculate the average power. The optimal value for N can be found with a full search.

III. Results and analysis

A 2.65 GHz 100 W LDMOS Doherty PA is used to test the performance of the proposed behavioral model. In order to mimic bursty usage patterns in future generation systems, the communications signal is a WiMAX-like signal consisting of two low power high power segments, each around 2 ms, repeated. The high power segment has 10 dB higher average power than the low power segment. In this work, two commonly used behavioral model structures are used for comparison, the memory polynomial model proposed in [8], and the generalized memory polynomial model [9].

The first step is to identify the length of the window that estimates the long term memory effect, N, from equation (4). In this work, 50000 samples are used in the offline identification stage and a full search is done which is then used for all further analysis. The result of this full search with $M = 2$ and $P = 5$ for the MP model can be seen in Fig. 2. A window size of around $N = 11000$ samples, which corresponds to around 0.35 ms, was found to be the optimal setting. This value relates to the thermal time constants as well as the parameters of the active bias circuit in the PA used.

In the first experiment, different model orders are used to evaluate the in-band performance – with the normalized mean square error (NMSE) – and the out-of-band performance – with the adjacent channel error power ratio (ACEPR) as defined in [10]. The data is captured at a 6 dB backoff from peak operating power. It is noticed that the proposed model has around 2.5 dB better in-band performance and around 3–4 dB better out-of-band performance for the different configurations. This can be explained by the capability of the proposed model to track the long term state (the change in input amplitude level and corresponding PA self-heating), while the normal memory polynomial model has to average the effect of the low and high power input segments, although mainly dominated by the higher power segments errors.

In Fig. 3, the instantaneous NMSE computed over blocks of 2000 samples for the models is shown. This experiment is done by first identifying the parameters of the models using the entire data set and then evaluating them blockwise on a separately measured set of data. The proposed model shows a consistent 2-4 dB better modeling performance than conventional models. The NMSE improvement is especially higher in the transitions between low and high power segments of the data, where PA behavior drifts are normally highest, and the proposed model has around 5 dB better NMSE. This can be explained because for identification of conventional models, all the different characteristic changes in the PA are averaged. It

TABLE I
COMPARISON OF THE PROPOSED MODEL AND MP AND GMP FOR DIFFERENT MODEL ORDERS. M IS THE MEMORY DEPTH.

(a) MP (values in dB)

Nonlinear order	MP NMSE	MP ACEPR	Proposed model NMSE	Proposed model ACEPR
	M = 4		M = 2	
P = 5	-46.8	-59.9	-49.4	-64.2
	M = 8		M = 4	
P = 5	-46.9	-59.9	-49.6	-64.4
	M = 4		M = 2	
P = 7	-47.9	-61.5	-49.7	-64.5

(b) GMP (values in dB). G in all models is 1

Nonlinear order	GMP NMSE	GMP ACEPR	Proposed model NMSE	Proposed model ACEPR
	M = 4		M = 2	
P = 5	-48.4	-62.4	-50.1	-65.6
	M = 8		M = 4	
P = 5	-48.5	-62.7	-50.2	-65.6
	M = 4		M = 2	
P = 7	-48.8	-62.7	-50.5	-65.9

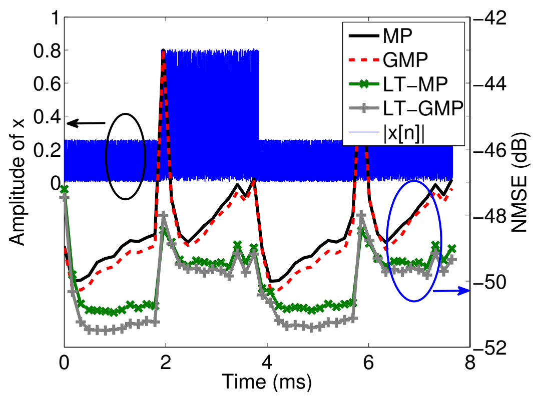

Fig. 3. Amplitude of input signal used (left axis), and comparison of model performance vs time (right axis). Model orders are chosen for relatively similar complexity of each model.

is also interesting to note that the performance of the proposed model for the beginning of the cycle is slightly worse. This is because the long term memory estimate is initialized at zero, and takes some time to ramp up to the correct values. This effect is not noticed in the second cycle as the long term memory estimate is consistent now.

Fig. 4 shows the NMSE vs number of parameters tradeoff for the models as proposed in [10]. It is noticed that except for the low parameter region, the proposed model has better modeling accuracy by around 2 dB compared to their traditional counterparts.

IV. CONCLUSIONS

In this work a new power amplifier behavioral model capable of modeling long term memory effects was presented. In particular, we demonstrated that it is well suited to handle bursty data which result as communication traffic shifts from voice to packet based data. The results show that by linearizing the parameters with respect to a long term memory term like

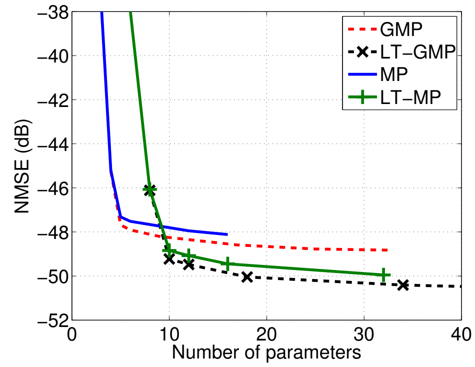

Fig. 4. The accuracy/complexity tradeoff for both models.

average power, it is possible to accurately track abrupt changes in input signals, and the modeling accuracy is improved by around 2.5 dB. The ability of the proposed model to track signal characteristic changes can be important for linearizing algorithms and digital predistortion, and can help lessen the load on parameter adaptation algorithms.

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