



International Journal of Engineering, Business and Enterprise Applications (IJEBA)

www.iasir.net

Modeling of Power Amplifier using Volterra Series

Ahlawat Amit^[1], Dhamija Ashutosh^[2], Gill Amandeep^[3]

Department of Electronics & Communication Engineering, GITM Bilaspur, Haryana, India^[1],

Department of Electronics & Communication Engineering, JMIT, Radaur, Haryana, India^[2],

Department of Electronics & Communication Engineering, JMIETI, Radaur, Haryana, India^[3],

Abstract: Conventional radio-frequency (RF) power amplifiers operating with wideband signals are particularly susceptible to the generation of out-of-band spurious emissions, also referred to as “spectral regrowth.” The power amplifier’s nonlinearity broadens the input signal’s bandwidth. This is known as Spectral regrowth and is undesirable. Spectral regrowth causes interference with adjacent channels and increases the probability of violations of the out of band emission requirements mandated by regulatory bodies. To analyze power amplifier for future communication system it is important to model the behavior of PA nonlinearity and memory effect accurately. Nonlinear amplifier behavioral models can be divided Into three types : memoryless (static), quasi memoryless and models with memory. In this paper we model the power amplifiers with Volterra series filters.

I. Introduction :

The numerous methods for modeling the nonlinear behavior of a device are classically divided into three categories: physical, empirical and table-based ones. Some may be difficult to categorize in this way, however, and therefore models[1] are divided here simply into physical and empirical ones, and into black-box and circuit-level ones. The Volterra series, a basis of empirical model that is still able to provide circuit-level information, is considered in this paper. Nonlinear Volterra theory was developed in the 1880s by Vito Volterra. The theory quickly received a great deal of attention in the field of electrical engineering, and then later in the biological field, as a powerful approach to the modeling of nonlinear system behavior. Volterra theory is a generalization of the linear convolution integral approach often applied to linear, time-invariant systems. The theory states that any time-invariant, nonlinear system can be modeled as an infinite sum of multidimensional convolution integrals of increasing order. This is represented symbolically by the series of integrals,

$$y(t) = h_0 + \int_0^\infty h_1(\tau_1)u(t-\tau_1)d\tau_1 + \int_0^\infty \int_0^\infty h_2(\tau_1, \tau_2)u(t-\tau_1)u(t-\tau_2)d\tau_1d\tau_2 + \dots$$

which is known as the Volterra series. Here, $u(t)$ represents the dynamic system input while $y(t)$ represents the system response. Volterra theory is based on dynamic data, and as such the average values of all input and response data sets are removed. Each of the convolution integrals contains a kernel, either linear (h_1) or nonlinear ($h_2, \dots, h_n$), which represents the behavior of the system. Knowledge of these kernels allows the prediction of a system’s response to any arbitrary input, and as such is critical to nonlinear Volterra modeling. The first term of the series represents the linear convolution integral. The first order term is considered to represent the mean of the system response. The term weakly nonlinear merely implies that a system is well represented by the first two or three terms of a Volterra series. All higher-order terms in this situation are seen to quickly tend toward zero, and are therefore negligible in the system representation. While Volterra theory has a strong foundation in both the biological and electrical engineering fields, it has received little attention in the field of aerodynamics until recently [2]. Linear response models have often been assumed sufficient for representation of nonlinear aerodynamic systems when excited by small perturbations. This assumption derives from the fact that highly nonlinear phenomena have a negligible impact on the net effect of various responses under conditions such as small perturbation excitation. In addition, the lack of attention is due in large part to the inherent difficulty of identifying Volterra kernels. Time is discretized with a set of time steps of equivalent size. Discrete time increments are indexed from 0

(time 0) to n (time t), and the evaluation of y at time n is denoted by $y[n]$. The convolution in discrete time is

$$y[n] = h_0 + \sum_{k=0}^N h_1[n-k]u[k] + \sum_{k_1=0}^N \sum_{k_2=0}^N h_2[n-k_1, n-k_2]u[k_1]u[k_2] + \dots$$

Where N is the total time record of interest.

Volterra kernels are the backbone of any Volterra series. Knowledge of a system's behavior is contained within these kernels, and given any arbitrary input the Volterra series can predict the response of the system.[3] Volterra kernels, both linear and nonlinear, are input dependent. As an example of this consider the case where the response of a linear system to an arbitrary input is desired. Here, the unit impulse response of the system to that type of input must first be defined. The first order kernel, h_1 , represents the linear unit impulse response of the system. This term is comparable to the basic frequency response function (FRF) of a linear system, transformed into the time domain. However, the kernel h_1 gives a more accurate portrayal of a system's linear response than does the FRF. This is because h_1 exists with the knowledge of higher-order, nonlinear terms while the FRF assumes a completely linear response. The second order kernel, h_2 , is a two-dimensional function of time. It represents the response of the system to two separate unit impulses applied at two varying points in time. Therefore the kernel is a function of both time and time lag. Similarly, h_3 is a three-dimensional function of time, representing the response of the system to three separate unit impulses applied at three varying points in time. Here the kernel is a function of time and two distinct time lags. It is through these time lags that nonlinear kernels represent the effect of a previous response as it is carried through time in the system. Volterra kernels can be rewritten in several ways simply by reordering the variables of integration. Because of this, more than one kernel can generally be used to describe a given system, and it is therefore necessary to impose uniqueness upon the kernels. This is accomplished by working with restricted forms of the kernels [4].

The truncated second-order Volterra series can be written as:

$$y(n) = h_0 + \sum_{k=0}^N h_1(n-k)u(k) + \sum_{k_1=0}^N \sum_{k_2=0}^N h_2(n-k_1, n-k_2)u(k_1)u(k_2)$$

$$y(t) = h_0 + \int_0^t h_1(t-\tau)u(\tau)d\tau + \int_0^t h_2(t-\tau_1, t-\tau_2)u(\tau_1)u(\tau_2)d\tau_1d\tau_2$$

Or

$$y[n] = u(0)s_1(n) + \sum_{k=1}^n s_1(n-k)(u(k) - u(k-1)) + u(0)^2 s_2(n, n) \\ + \sum_{k_1=1}^n \sum_{k_2=1}^n s_2(n-k_1, n-k_2)(u(k_1) - u(k_1-1))(u(k_2) - u(k_2-1))$$

Where $s_1[n]$ and $s_2[n]$ are the first- and second-order kernels, respectively, $u[n]$ is a general time-dependent input signal, and $y[n]$ is the system's response. Silva showed that the nonlinear Navier-Stokes equations can be considered weakly nonlinear, i.e., can be accurately represented by a truncated second order Volterra series, neglecting higher kernels.

II. First/Second Order of Volterra Kernel Identification

Let $u_0(t) = \delta(t)$ and $u_1(t) = \delta(t) + \delta(t+T)$

where $\delta(t)$ is the Diract's delta function.

Then, the responses due to the inputs will be expressed as

$$y_0(t) = h_0 + \int_0^t h_1(t-\tau)\delta(\tau)d\tau + \int_0^t \int_0^t h_2(t-\tau_1, t-\tau_2)\delta(\tau_1)\delta(\tau_2)d\tau_1d\tau_2$$

$$y_1(t) = h_0 + \int_0^t h_1(t-\tau)(\delta(\tau) + \delta(\tau+T))d\tau \\ + \int_0^t \int_0^t h_2(t-\tau_1, t-\tau_2)(\delta(\tau_1) + \delta(\tau_1+T))(\delta(\tau_2) + \delta(\tau_2+T))d\tau_1d\tau_2$$

If we assume that $h_0 = 0$,

$$y_0(t) = h_1(t) + h_2(t, t)$$

$$y_1(t) = h_1(t) + h_1(t+T) + h_2(t, t) + 2h_2(t, t+T) + h_2(t+T, t+T)$$

Since $h_2(t, t+T) = h_2(t+T, t)$,

$$y_1(t) = y_0(t) + h_1(t+T) + 2h_2(t, t+T) + h_2(t+T, t+T)$$

$$y_0(t+T) = h_1(t+T) + h_2(t+T, t+T)$$

Therefore,

$$y_1(t) = y_0(t) + y_0(t+T) + 2h_2(t, t+T)$$

The second order of the Volterra kernel will be determined as

$$h_2(t, t+T) = \frac{1}{2}(y_1(t) - y_0(t) - y_0(t+T))$$

Now, let's assume that $T = 0$. Then,

$$h_2(t, t) = \frac{1}{2}(y_1(t) - y_0(t) - y_0(t))$$

If we put $u_0(t) = 2\delta(t)$ as an input. The response will be

$$y_2(t) = h_0 + \int_0^t h_1(t-\tau)2\delta(\tau)d\tau + \int_0^t \int_0^t h_2(t-\tau_1, t-\tau_2)2\delta(\tau_1)2\delta(\tau_2)d\tau_1d\tau_2 \\ = 2h_1(t) + 4h_2(t, t)$$

$$h_2(t, t) = \frac{1}{2}(y_2(t) - 2y_0(t))$$

Since

$$y_2(t) = 2h_1(t) + 4h_2(t, t)$$

From the above equation, the first order of the Volterra kernel will be

$$h_1(t) = 2y_0(t) - \frac{1}{2}y_2(t)$$

where $y_0(t)$ is the response due to $\delta(t)$ and $y_2(t)$ is the response due to $2\delta(t)$.

III. First Order Series Approximation

Raveh, et al further assumed that the response can be evaluated only with the first term in Volterra kernel. The response of the system can then be evaluated by convolving the impulse response $h(n)$ with the input signal:

$$y(n) = h(0) + \sum_{k=0}^n h(n-k)u(k) \quad n = 0, 1, 2, \dots$$

Or the response of the system to an arbitrary input is computed by convolution of the step response $s(n)$ with the derivative of input signal $u(n)$, according to Duhamel's integral:

$$\begin{aligned} y(n) &= u(0)s(n) + \sum_{k=1}^n s(n-k)(u(k) - u(k-1)) \\ &= u(0)s(n) + \sum_{k=1}^n s(n-k)\dot{u}(k)\Delta t \quad n = 0, 1, 2, \dots \end{aligned}$$

IV. Result:

Frequency plots for power amplifiers without using volterra modeling and with volterra modeling:

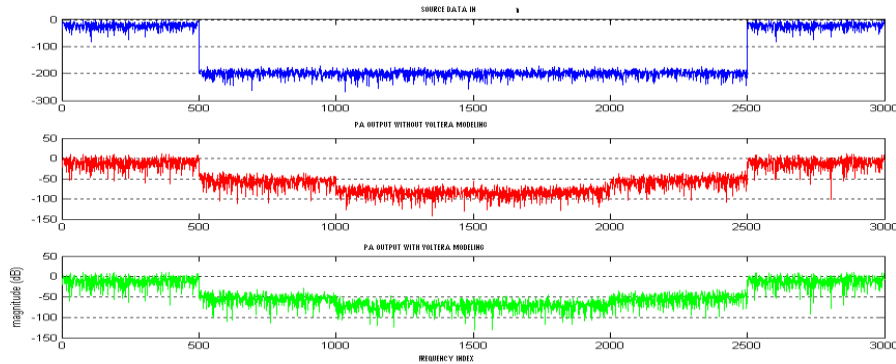


Fig 1

V. Conclusion:

In this paper we have compare the power amplifier frequency plots with and without using using volterra modeling.the results with using volters filters are far better compared to the results without volterra filters.

VI. References:

- [1]. An Approximation of Volterra Series Using Delay Envelopes, Applied to Digital Predistortion of RF Power Amplifiers With Memory Effects, Nima Safari, *Student Member, IEEE*, Terje Røste, *Member, IEEE*, Pavlo Fedorenko, *Student Member, IEEE*, and J. Stevenson Kenney, Senior Member, IEEE, VOL. 18, NO. 2, FEBRUARY 2008
- [2]. Euns, C.; Powers, E.J.: A new Volterra predistorter based on the indirect learning architecture. IEEE Tran. On Signal Processing 45 (1997), 223-227.

- [3]. Zhu, A.; Brazil, T.J.: An adaptive Volterra predistorter for the linearization of RF high power amplifiers. MTT-IMS 2002 1 (2002), 461-464.
- [4]. Stapleton, S. P. and Cavers, J. K., "A new technique for adaptation of linearizing predistorters," in Proc. IEEE Veh. Technol. Conf., pp. 753–758,