

Digital Pre-Distorter Based On A Box Oriented Memory Polynomial Model and Optimized By Tabu Search Algorithm for Wimax Radio Frequency Power Amplifier

Harjinder Singh^{#1}, Amandeep Singh Sappal^{#2}

^{#1} Department of Electronics and Communication Engineering, Punjabi University, Patiala, India

^{#2} Department of Electronics and Communication Engineering, Punjabi University, Patiala, India

Abstract- Digital predistortion (DPD) technique is widely used to linearize a radio frequency power amplifier (PA). It is the fastest and cost effective digital processing technique to moderate the distortions in PA caused by nonlinearity and memory effects. Digital predistorter is inverse of the PA, so the design of a digital predistorter requires the accurate identification of PA's behavior. This paper presents a box oriented memory polynomial DPD technique based on an indirect learning approach. The adjacent channel leakage ratio (ACLR), error vector magnitude (EVM) and number coefficients of the PA and digital predistorter are evaluated of the proposed model. The coefficients of PA and DPD are optimized iteratively in order to minimize the output PSD around the pre specified frequency. In the proposed work metaheuristic optimization algorithm called tabu search algorithm (TSA) is used to optimize the coefficients of PA and digital predistorter. This approach reduced the complexity and cost of DPD technique implementation. The TSA produces hopeful results for Worldwide Interoperability of Microwave Access (WiMAX) signal.

Keywords- Power Amplifier, Memory Polynomial, Digital Predistorter, tabu search algorithm, radio frequency, WiMAX, Power Spectral Density etc.

I. INTRODUCTION

AM-AM and AM-PM characteristics of digital predistorter are inverse AM-AM and AM-PM characteristics of PA respectively. So, box oriented memory polynomial or memory polynomial is the best linearization technique to model digital predistorter as per PA [1-3, 11-13]. The predistorter coefficients can be estimated using direct learning or indirect learning architecture. System identification of the nonlinear physical system is not necessary in the indirect learning architecture as compared to direct learning architecture [12-14]. So, in this work indirect learning architecture

has been used. Modern wireless communication systems like WiMAX, LTE, are continuously developing in data rate and bandwidth to support more users and provide more data services [1]. As the bandwidth increases, it poses rigorous requirements on the PA linearity, efficiency and memory effects. DPD technique is a widely used technique to compensate the nonlinearity and memory effect of radio frequency (RF) PA [15, 16]. To effectively developed DPD at first an accurate PA model must be developed and the nonlinear characteristics of the PA are accurately modeled, the cascade of DPD+PA can become linear [2,17,18]. After approximating the nonlinear part by a piecewise linear function, its coefficients are estimated by using TSA. The first section of this paper is introduction, second section describes box oriented memory polynomial modeling of PA and DPD, section third contains TSA and its explanation, simulation results are described in fourth section at the last conclusion[4,19].

II. Box Oriented Memory Polynomial Model

In this paper, the box oriented memory polynomial modeling of PA and DPD has been used. Memory polynomial model is one of the most popular choices for the behavioural of non-linear system with memory. The box oriented Memory Polynomial model implemented in the proposed work shown in figure 1.

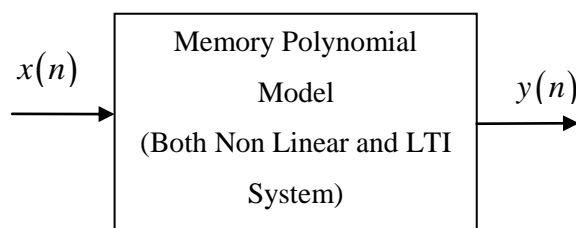


Figure 1: Box oriented Memory Polynomial model

The expression for the output $(y(n))$ is given by [12]

$$y(n) = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} c_{l,k} x(n-l) |x(n-l)|^k \quad (1)$$

A memory polynomial model consists of a double summation over two parameters; the memory length L and the nonlinearity order K , which account for the model's flexibility

where the signals $x(n)$ and $(y(n))$ are the complex baseband input and output waveforms, respectively, and $c_{l,k}$ represents the model's coefficients. L represents memory length and K is the order of non-linearity.

III. Tabu search algorithm

Fred W. Glover in formed TSA metaheuristic search method for optimization. TSA enhances the performance of local search by relaxing its basic rule [7,10]. It uses a local or neighborhood search procedure to move iteratively from one potential solution to an improved solution in the neighborhood of until some stopping criterion has been satisfied (generally, an attempt limit or a score threshold). The most important distinguishing property of TSA is the exploitation of adaptive forms of memory. So, the solutions admitted to the new neighborhood is determined through the use of memory structures [6,7].

These memory structures form can be classified a short term types of memory, Long-term types of memory and intermediate term types of memory but These memory structures form can overlap in practice. In Short term memory structures, potential solution appears on the tabu list cannot be revisited until it reaches an expiration point. Intermediate term memory structure intensification rules intended to bias the search towards promising areas of the search space. But in Long term, diversification rules that drive the search into new regions when the search becomes stuck in a plateau or a suboptimal dead end [6-8]. Using these memory structures, the search progresses by iteratively moving from the current solution to an improved solution. Within these categories, memory can further be differentiated by measures such as frequency and impact of changes made. Short term memory alone may be enough to achieve solution superior to those found by conventional local search methods, but intermediate and long-term structures are often necessary for solving harder problems. The flowchart of TS algorithm is shown in figure 2 [7-9].

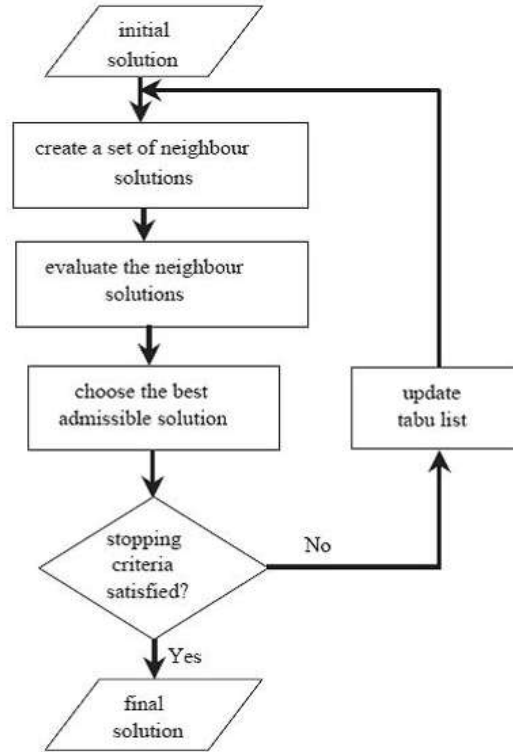


Figure 2: Flow chart of tabu search algorithm

The basic elements of TS are summarized as.

f real-valued function, S a given set, i current solution, j next solution, i^* the best solution, k the iteration counter, $N(i)$ neighborhood, $j = i \oplus m$ a notation applied to i in order to obtain a new solution j , V^* a Generated subset V^* of solution in $N(i)$, m tabu move applied to a current solution i , T tabu list, T_r several lists at a time, t_r some constituents of i or of m currently not allowed to be involved in a move, $t_r(i, m) \in T_r$. A move m (applied to a solution i) will be a tabu move if all conditions are satisfied, $a(i, m)$ an aspiration level which is better than a threshold value $A(i, m)$ and $a_r(i, m) \in A_r(i, m)$ conditions of aspiration. TSA can be directly applied to virtually any kind of optimization problem, most of these problems in the following form, where “optimize” means to minimize or maximize. Optimize $f(x)$ Subject to $x \in X$ [7,10].

The function $f(x)$ may be linear, nonlinear or even stochastic, and the set X summarizes constraints on the vector of decision variables x . The constraints may

similarly include linear, nonlinear or stochastic inequalities, and may compel all or some components of x to receive discrete values. The TSA with a simple descent method is to minimize $f(x)$. The final x obtained by a descent method is called a local optimum, since it is at least as good as or better than all solutions in its neighborhood. Given a matrix of weights $E = \{e_{i,j}\}_{m \times m}$, the linear ordering problem (LOP) consists of finding a permutation p of the columns (and rows) in order to maximize the sum of the weights in the upper triangle [8,9]. In mathematical terms, it can be written as;

$$C_E(p) = \sum_{i=j}^{m-1} \sum_{j=i+1}^m e_{p_i p_j} \quad (2)$$

In this equation p_i is the index of the column (and row) in position i in the permutation. Note that in the LOP, the permutation p provides the ordering of both the columns and the rows. The TSA emphasis on adaptive memory makes it possible to exploit the types of strategies that underlie the best of human problem-solving, instead of being confined to mimicking the processes found in lower orders of natural phenomena and behavior [6-9].

The following pseudocode presents for the TS algorithm as described above [6-8].

Tabu search

Step 1. choose an initial solution i in S . Set $i^* = i$ and $k = 1$.

Step 2. Set $k = k + 1$ and generate a subset V^* of solution in $N(i, k)$ such that either one of the tabu conditions $t_r(i, m) \in T_r$ is violated ($r = 1, \dots, t$) or at least one of the aspiration conditions $a_r(i, m) \in A_r(i, m)$ holds ($r = 1, \dots, a$)

Step 3. Choose a best $j = i \oplus m$ in V^* (with respect to f) and set $i = j$

Step 4. If $f(i) < f(i^*)$ then set $i^* = i$.

Step 5. Update tabu and aspiration conditions.

Step 6. If a stopping condition is met then stops. Else go to Step 2.

TSA kept the information on the itinerary through the last solutions visited. Such information will be used to guide the move from i to the next solution j to be chosen in $N(i)$. The role of the memory will be to restrict the choice to some subset of $N(i)$ by forbidding for instance moves to some neighbor

solutions. This systematic use of memory is an essential feature of TSA. While most exploration methods keep in memory essentially the value $f(i^*)$ of the best solution i^* visited so far, If such a memory is introduced, consider that the structure of $N(i)$ will depend upon the program and hence upon the iteration k ; so it may refer to $N(i, k)$ instead of $N(i)$.

There will describe the exploration process in S in terms of moves from one solution to the next. For each solution i in S , define $M(i)$ as the set of moves which can be applied to i in order to obtain a new solution j ($j = i \oplus m$) [7-9].

A tabu list (T) of the last $|T|$ solutions visited will prevent cycles of size at most $|T|$. So instead of keeping a list T of the last $|T|$ solutions visited, it may simply keep track of the last $|T|$ moves or of the last $|T|$ reverse moves associated with the moves actually performed. When a number of lists T_r at a time, Then some constituents t_r (of i or of m) will be given a tabu status to indicate that these constituents are currently not allowed to be involved in a move. So a collection of tabu conditions formulate as follows ($r = 1, \dots, t$) [8-10];

$$t_r(i, m) \in T_r \quad (3)$$

A move m (applied to a solution i) will be a tabu move if all conditions are satisfied an aspiration level $a(i, m)$ which is better than a threshold value $A(i, m)$.

Generally $A(i, m)$ can be viewed as a set of preferred values for a function $a(i, m)$. So conditions of aspiration can be written in the form ($r = 1, \dots, t$);

$$a_r(i, m) \in A_r(i, m) \quad (4)$$

If at least one of these conditions is satisfied by the tabu move m applied to i , then m will be accepted (in spite of its status). TSA algorithm can be terminated, after a fixed number of iterations or after some number of iterations without an improvement in the objective function value or when the objective reaches a pre-specified threshold value [6-9].

IV. Simulation Results

To validate the performance of the TSA, the PA and DPD was modeled using the memory polynomial model given by equation 1. All the characteristics of proposed algorithms for PA and DPD have been measured by sweeping value of memory length L between 1 to 5 and the nonlinearity order K between 2 to 7 in memory polynomial.

PA modeling using TSA

Figure 3 and figure 4 shows the AM-AM characteristics and the AM-PM characteristics respectively of actual PA and proposed TSA PA model, the characteristics curve of proposed TSA PA model is tried to follow the characteristics of actual PA. This shows the accuracy of the modeling in terms of AM-AM and AM-PM characteristics.

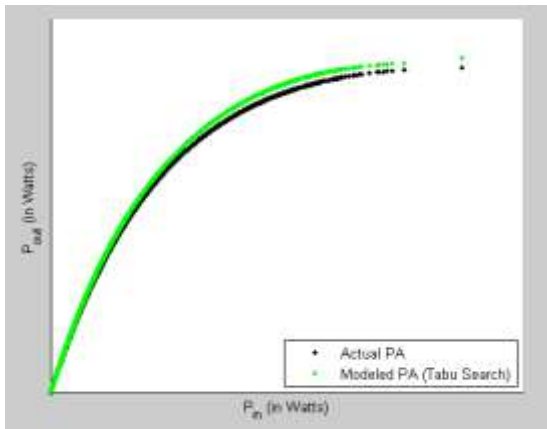


Figure 3: AM-AM characteristics for actual PA and proposed TSA PA model

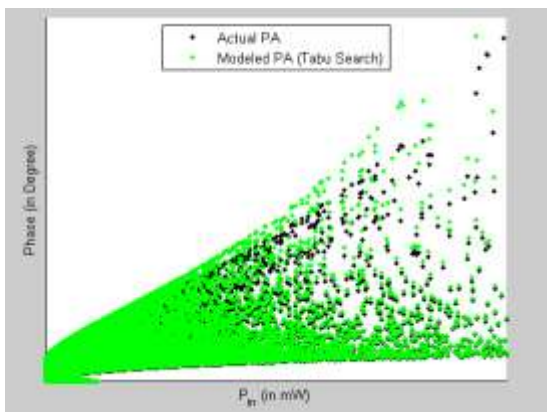


Figure 4: AM-PM characteristics for actual PA and proposed TSA PA model

Figure 5 shows the power spectral density diagram of actual PA and proposed TSA PA model, due to PA memory and non-linear effects, the spectrum of output signal has expanded.

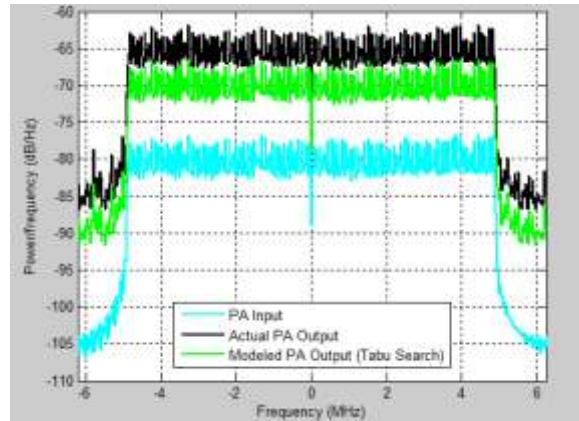


Figure 5: Power spectral density of actual and proposed TSA PA model

The performance of proposed TSA PA model based on ACLR (dB), EVM (dB), memory length and non linear order can be inferred from table 1. The ACLRs of actual PA are Lower Channel 2 (53.17), Lower Channel 1 (28.28), Upper Channel 1 (29.04) and Upper Channel 2 (54.01). The ACLRs of modeled PA using TSA is Lower Channel 2 (55.04), Lower Channel 1 (29.11), Upper Channel 1 (28.65) and Upper Channel 2 (55.13).

Table 1: Measurements of actual PA and proposed TSA modeled PA

Type	Adjacent Channel Leakage Ratio (dB)				Error Vector Magnitude (dB)	Memory length	Non linear order
	Lower Channel 2	Lower Channel 1	Upper Channel 1	Upper Channel 2			
Actual PA	53.17	28.28	29.04	54.01	-24.28	-	-
TSA PA	55.04	29.11	28.65	55.13	-25.12	4	7

From table 1, it has been concluded that all ACLRs of TSA modelled PA have closer to the ACLRs of actual PA. For TSA PA model, the values of memory length

L and the nonlinearity order K are 4 and 7 respectively so, the no of coefficients are 28 in TSA PA model. The EVM of actual PA and TSA are -24.28 and -25.12 respectively, so the EVM of TSA PA model (-25.12) is also closer to EVM of actual PA (-24.28).

DPD modeling using TSA

Figure 6 shows the inverse AM-AM characteristics of actual PA and proposed TSA DPD model. The characteristics curves of proposed TSA modeled digital predistorter is tried to follow the inverse characteristics of actual PA, this shows the accuracy of the modeled TSA digital predistorter.

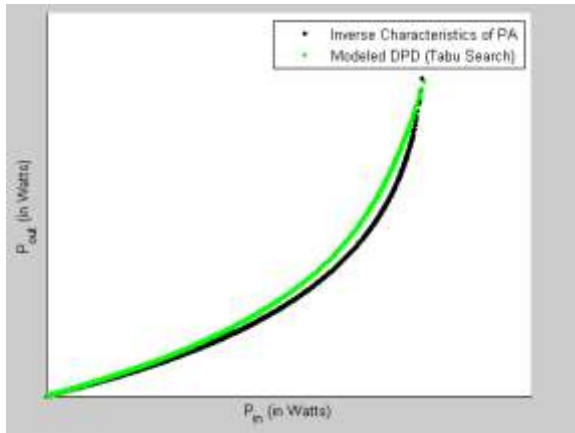


Figure 6: AM-AM characteristics for proposed TSA PA model and inverse AM-AM characteristics of actual PA

Figure 7 shows the power spectral density diagram of actual PA and digital predistorters of proposed TSA, due to PA memory and non-linear effects, the spectrum of output signal has expanded.

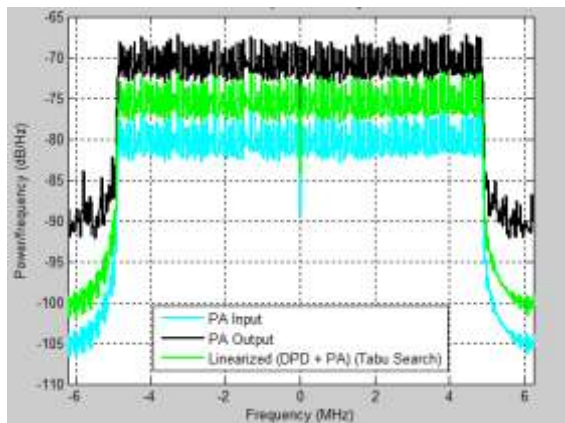


Figure 7: Power spectral density of actual and modelled PA, modelled (DPD+PA) using proposed TSA

The performance comparison of the proposed TSA digital predistorters based on ACLR (dB), EVM

(dB), memory length and non linear order can be inferred from table 2. The ACLRs of modeled digital predistorter using TSA is Lower Channel 2 (80.32), Lower Channel 1 (56.62), Upper Channel 1 (57.17) and Upper Channel 2 (81.27). The ACLRs of actual PA are Lower Channel 2 (53.17), Lower Channel 1 (28.28), Upper Channel 1 (29.04) and Upper Channel 2 (54.01).

Table 2: DPD Performance Metrics using using proposed TSA modeled DPD

Type	Adjacent Channel Leakage Ratio (dB)				Error Vector Magnitude (dB)	Memory length	Non linear order
	Lower Channel 2	Lower Channel 1	Upper Channel 1	Upper Channel 2			
Actual PA	53.17	28.28	29.04	54.01	-24.28	-	-
TSA DPD	80.32	56.62	57.17	81.27	-28.31	4	7

From table 2, it has been concluded that the improvement in all ACLRs (Lower Channel 2 (27.15dB), Lower Channel 1 (28.34dB), Upper Channel 1 (28.13dB) and Upper Channel 2 (27.26dB)) of TSA digital predistorter with respect to the actual PA all ACLRs. For TSA DPD model, the values of memory length L and the nonlinearity order K are 4 and 7 respectively so, the no of coefficients are 28 in TSA DPD model. The EVM of actual PA and TSA PA model are -24.28 and -28.31 respectively, so the EVM (-4.03dB) of TSA DPD model has been improved with respect to the EVM of actual PA.

Conclusion

The PA and DPD model extraction solution based on a metaheuristic optimization algorithm shows the sovereignty of TSA. The performance of proposed algorithm was tested on a wideband power amplifier working for a WiMAX communication system. The PA results show the ACLR and EVM of modeled PA are very close to the actual PA, this shows the accuracy of proposed PA model. The DPD results concluded that 27- 28 dB improvement in ACLR and EVM has also improved. The number of coefficients is also less in proposed PA and DPD model.

REFERENCES

- [1]. Z. Shen, A. Papasakellariou, J. Montojo, and F. Xu (2012). Overview of 3GPP LTE advanced carrier aggregation for 4G wireless communications. *IEEE Communication Mag*, 50, 122-130.
- [2]. F. M. Ghannouchi and O. Hammi (2009). Behavioral modeling and predistortion. *IEEE Microwave Magazine*, 10, 52-64.
- [3]. W. Bösch and G. Gatti (1989). Measurement and simulation of memory effects in predistortion linearizers. *IEEE Trans. Microwave TheoryTech*, 37(12), 1885–1890.
- [4]. D. R. Morgan, Z. Ma, J. Kim, M. G. Zierdt, and J. Pastalan (2006). A generalized memory polynomial model for digital predistortion of RF power amplifiers. *IEEE Transactions in Signal Processing*, 54, 3852–3860.
- [5]. Rajbir Kaur (2016). Design and Implementation of An Efficient Digital Pre-Distorter for Wideband Wireless Transmitters, Doctoral Thesis. *Faculty of Engineering and Technology, Punjabi University, Patiala*.
- [6]. Glover, F. and M. Laguna (1993). Tabu Search, *Modern Heuristic Techniques for Combinatorial Problems*, C. Reeves, ed., Blackwell Scientific Publishing, 70-141.
- [7]. Fred Glover. Tabu search fundamentals and uses, US West Chair in Systems Science Graduate School of Business, *Boulder, Colorado* 80309-0419, June 1995.
- [8]. Hertz, A. and D. de Werra (1991). The Tabu Search Metaheuristic: How We Used It, *Annals of Mathematics and Artificial Intelligence*, 1, 111-121.
- [9]. Hubscher, R. and F. Glover (1994). Applying Tabu Search with Influential Diversification to Multiprocessor Scheduling, *Computers and Operations Research*, Vol. 21, No. 8, pp. 877-884.
- [10]. Glover, F. and A. Lokketangen (1994). "Probabilistic Tabu Search for Zero-One Mixed Integer Programming Problems," University of Colorado, Boulder.
- [11]. Amandeep Singh Sappal, Dr. Manjeet Singh Patterh and Dr. Sanjay Sharma (2011). Fast Complex Memory Polynomial Based Adaptive Digital Pre-Distorter. *International Journal of Electronics, (Taylor and Francis)*, 98(7), 923-931.
- [12]. Yao X., Wang F., Padmanabhan K., and S. Salcedo-Sanz S. (2005). Hybrid evolutionary approaches to terminal assignment in communications networks. *Recent Advances in Memetic Algorithms, Studies in Fuzziness and Soft Computing*, 166(0), 129–159.
- [13]. NavidLashkarian, Jun Shi, and Marcellus Forbes (2014). A Direct Learning Adaptive Scheme for Power-Amplifier Linearization Based on Wirtinger Calculus. *IEEE Transactions on Circuits and Systems-I*, 61(12), 3496-3505.
- [14]. I. Zhang, Youjiang Liu, Jie Zhou, ShuboJin, Wenhua Chen and Silong Zhang (2015). A Band-Divided Memory Polynomial for Wideband Digital Predistortion With Limited Bandwidth Feedback. *IEEE Transactions on Circuits and Systems-II*: 62(10), 922-925,
- [15]. Harjinder Singh and Amandeep Sappal (2015). Modeling and compensation of thermal effects in power amplifiers. *IEEE Conference in Computing and Communication (IEMCON)*, Vancouver, 1-7,
- [16]. SouhirLajnef, NoureddineBoulejfen, Abubaker Abdelhafiz and Fadhel M. Ghannouchi (2016). Two-Dimensional Cartesian Memory Polynomial Model for Nonlinearity and I/Q Imperfection Compensation in Concurrent Dual-Band Transmitters. *IEEE Transactions on Circuits and Systems-II*, 63(1), 14-18.
- [17]. Nikolai Wolff, Wolfgang Heinrich and Olof Bengtsson (2016). A Novel Model for Digital Predistortion of Discrete Level Supply-Modulated RF Power Amplifiers. *IEEE Microwave and Wireless Components Letters*, 26(2), 146-148.
- [18]. Lie Zhang and Yan Feng (2016). An Improved Digital Predistortion in Wideband Wireless Transmitters Using an Under-Sampled Feedback Loop. *IEEE Communications Letters*, 20(5), 910-913.
- [19]. Li Gan (2009). Adaptive Digital Predistortion of Nonlinear Systems. Doctoral Thesis. *Faculty of Electrical and Information Engineering, Graz University of Technology, Austria*.