# A New Pre-distorter for Linearizing Power Amplifiers Using Adaptive Genetic Algorithm

**P.R. Bipin, P.V. Rao and S. Aruna**

**Abstract** The power amplifier (PA) is naturally nonlinear in its operation. To get good energy efficiency, the PA is needed to function at its saturation level and results in the generation of the nonlinear outputs. To counter the nonlinearization in PA, a pre-distorter is appropriately designed and introduced in front of the PA. In this paper, an innovative pre-distorter is introduced by employing adaptive genetic algorithm (AGA) and their results are compared with that of genetic algorithm (GA) and particle swarm optimization (PSO) algorithm. The Wiener model is considered to model the PA, and the pre-distorter is built up by means of Hammerstein model. The new approach simulated using MATLAB and the outputs achieved are analyzed. The pre-distortion using AGA has produced better results in terms of MSE compared to that produced using PSO and GA optimization algorithms.

**Keywords** Digital pre-distorter · Particle swarm optimization
Adaptive genetic algorithm · Wiener model

## 1 Introduction

Power amplifiers (PAs) are the important subunits in almost all the wireless communication systems. PAs are designed to boost the power level of the signal before transmitting it through the antenna. They also show the memory effects [1], which is not desirable. Further, they tend to be invariably nonlinear. The amplifiers which

P.R. Bipin (✉)
Department of ECE, VTU Belgaum, Belgaum, Karnataka, India
e-mail: bipinpr@gmail.com

P.V. Rao · S. Aruna
Rajarajeswari College of Engineering, Bengaluru, India
e-mail: pachararao@rediffmail.com

S. Aruna
e-mail: arunaraman6@gmail.com



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are incredibly linear with good efficiency have become a rare specimen. The pre-distorter recompenses for the nonlinear distortion envisaged by the PA by working on the input signal. The theory of the digital pre-distorter (DPD) is easy to comprehend. Here, a nonlinear distortion function is generated within the digital horizon which represents the inverse of the amplifier function [2]. The DPD will be connected in front of the PA. In fact, it is very easy to devise an incredibly linear and inferior distortion system in principle, by connecting the two nonlinear systems (DPD and PA) in series.

The process followed in this paper offers the pre-distortion before the power amplifier with the help of the optimization method to achieve linearity in the combined system. The PA is modeled using Wiener model, and the pre-distorter is designed using Hammerstein model. At the output of Wiener HPA model, the authentic constraint vector is achieved and it is optimized by means of optimization approaches [3] such as particle swarm optimization (PSO) [4], genetic algorithm (GA) and adaptive genetic algorithms (AGA). In Sect. 2, a brief account of the Wiener HPA model and basics of PSO, GA, and AGA are given which is used for the optimization of Wiener HPA results to devise a pre-distorter. Test outcomes and consequential appraisal are presented in Sect. 3. Finally, the conclusions are effectively exhibited in Sect. 4.

# 2 Methodology

## 2.1 Power Amplifier Modeling

The PA model used here is the Wiener model which incorporates a memoryless nonlinearity preceded by a linear filter [2]. The inverse of Wiener model can be easily obtained by using Hammerstein model (a linear filter preceded by a memoryless nonlinearity).

The linear filter coefficient vector for the liner filter with order $K_l$ can be denoted by

$$h = [h_0 h_1 \ldots h_{K_l}]^{\mathrm{T}} \tag{1}$$

The PA provides amplitude and phase distortion to the input signal applied to it [5], and this can be considered as the traveling wave tube (TWT) nonlinearity. Let $t = \left[\alpha_a \beta_a \alpha_{\varnothing} \beta_{\varnothing}\right]^{\mathrm{T}}$ gives the parameter vector for TWT nonlinearity [6] where $\alpha_{a,} \beta_a \alpha_{\varnothing} \beta_{\varnothing}$ are different parameters of the TWT nonlinearity.

## 2.2 Wiener Model Identification

For the Wiener parameter identification purpose, a normalized 64-QAM signal was generated and is then applied to Wiener model to construct training data set $\{x(k), y(k)\}$, where $x(k)$ is the input QAM and $y(k)$ is the output from the model, and the diagram is shown in Fig. 1. The true parameter of memory high-power amplifier is estimated using the training data. The true parameter vector is defined as

$$\beta = \left[\beta_1 \beta_2 \ldots \beta_{N_\beta}\right]^{\mathrm{T}} \tag{2}$$

where $N_\beta$ represents the total number of parameter to be estimated, that is, the sum of number of linear filter coefficients and number of nonlinearity coefficients. The training data input $x(k)$ is given to the model and it produces an output $y(k)$. The output from the estimated Wiener model is indicated as $\hat{y}(k)$. The error results between the desired output $y(k)$ and the model output $\hat{y}(k)$ is $e(k) = y(k) - \hat{y}(k)$; thus, mean-square error cost function can be given by

$$J\left(\tilde{\beta}\right) = \frac{1}{K}\sum_{k=1}^{K} |e(k)|^2 \tag{3}$$

The true parameter vector $\beta$ is estimated by obtaining the solution to the following optimization problem

$$\hat{\beta} = \arg\,\min_{\hat{\beta}\in\varnothing} J\left(\tilde{\beta}\right) \tag{4}$$

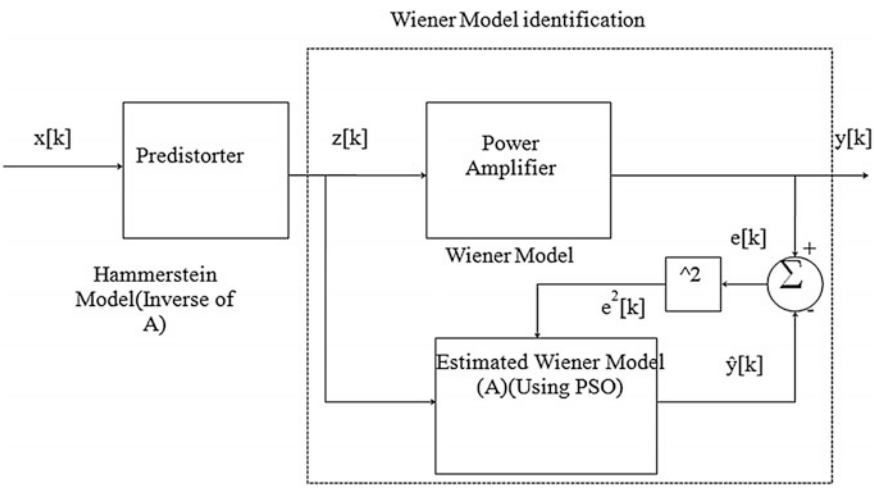


**Fig. 1** Wiener model identification

where $\varnothing$ the search space is given as

$$\varnothing \triangleq \prod_{i=1}^{N_\beta} \left[\beta_{i,\min} \beta_{i,\max}\right] \quad (5)$$

The true parameter $\beta$ is an element of the search space. The cost function (3) is a nonlinear function and has local minima. The above challenging identification problem is solved here using PSO algorithm, GA, and AGA.

### *2.3 Genetic Algorithm (GA)*

The genetic algorithm [7] represents an adaptive global search technique in accordance with the evolutionary data of genetics. For the purpose of solving the optimization challenges, the genetic algorithm is effectively utilized as an arbitrary search technique. In the GA, the iterations are represented as the generation of modernized solutions and the population is characterized as the chromosomes.

### *2.4 Adaptive Genetic Algorithm (AGA)*

The authentic constraint is achieved after the Wiener HPA model is adapted. The original population is allotted by the authentic constraint output. The traditional genetic algorithm is optimized by means of the mutation operator. The mutation function carried out in the innovative technique is the Cauchy mutation. The adaptive genetic algorithm is carried out by means of the steps detailed below:

1. Initialization:
   - Arbitrarily produce an initial population of individuals by employing a symbolic illustration technique.
2. Generate Fitness Function:
   - Estimate the fitness of the individuals by calculating the bond energy of the candidate solutions characterized by them.
   - Choose a pair of individuals from the present population by employing a conventional roulette wheel selection operator (step A).
3. Crossover Operation:
   - The chosen individuals are reassembled to create a pair of offspring by employing the partially matched crossover in accordance with the crossover rates.

- Appraise the fitness of the two offspring by evaluating the bond energy of the candidate solutions characterized by them.
- Place on record the percentage of perfection, or the percentage of deprivation, on their fitness values on account of the crossover function.

4. Mutation Operation:

- Carry out the process of the conventional symbolic mutation of the two offspring and appraise their fitness by evaluating the bond energy of the candidate solutions characterized by them.
- Place on record the percentage of perfection, or the percentage of deprivation, of their fitness values as a consequence of the mutation function.

Subsequent to the crossover function, the procedure of mutation is performed where the new chromosomes with the finest fitness values are mutated. In the novel technique, the Cauchy mutation is effectively employed for mutating the genes in the parent chromosomes.

In the Cauchy mutation, the optimal solution is achieved by moving each gene left in the parent chromosome and is replaced with the newer located genes. Now, the gene of the parent chromosome is moved one step left and the optimized new solution is achieved when the mutation procedure is concluded.

5. Updating Population:

- Allot the consequential individuals into a fresh population pool. If the population size is not achieved, go back to step A.
- Adapt the crossover and mutation rates according to the specified rules.

6. Termination:

- Verify the stopping criterion.
- End the genetic investigation procedure and select the best candidate solution over time as the ultimate solution if the stopping criterion is fulfilled.
- Or else, move forward to the succeeding generation with the old population to be substituted by the new population, and go back to step A.

The AGA-optimized Wiener HPA pattern is effectively employed to devise a pre-distorter model which is exploited to scale down the nonlinear attributes.

## *2.5 Pre-distorter Design*

The pre-distorter is implemented using Hammerstein model as it represents the inverse form of the Wiener model. The linear filter of Hammerstein model [8] is made to be inverse of linear filter of identified Wiener power amplifier model, and inverse nonlinearity [9] of estimated Wiener is used to implement the Hammerstein nonlinearity.

Consider the transfer function of the Hammerstein Pre-distorter's linear filter.

$$Q(z) = z^{-\tau} \sum_{i=0}^{N_h} q_i z^{-i} \tag{6}$$

where $q_i$ represents the linear filter coefficient and $\tau$ is the delay. If $H(z)$ is the transfer function of linear filter of Wiener model and is a minimum phase filter, then $\tau = 0$. The filter coefficient of pre-distorter can be obtained by solving the linear equations derived from

$$Q(z).H(z) = z^{-\tau} \tag{7}$$

## 3 Results and Discussions

Figure 2 exhibits the output signal $y(k)$ of the memory power amplifier when normalized 64-QAM signal, $x(k)$, is given to its input for input back-off value of 5 dB. It is evident from the figure that output signal is spread around the input signal as a result of memory effect and nonlinearity of power amplifier. It will lead to larger bit-error rate and adjacent channel interference during transmission.

In this paper, identification process is done using both PSO algorithm and GA and AGA algorithms. The training data set taken contains 500 samples of normalized 64 QAM data. The noise with standard deviation 0.0 and 0.01 was added as input, and identification was done for different IBO values such as 5, 10, 15 dB. The results obtained were averaged over 100 runs.

The parameter vector for the estimated Wiener power amplifier model obtained for each case is given by

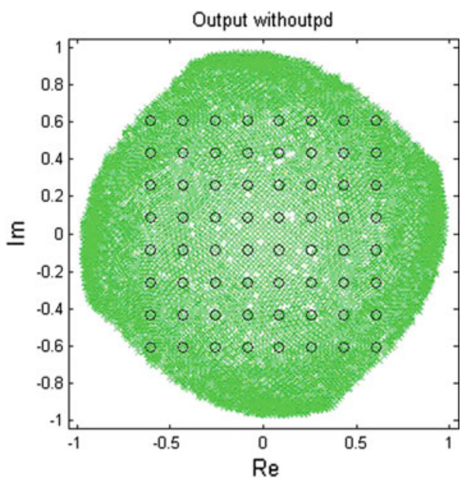


**Fig. 2** Output without pre-distorter

$h^T$ = [0.777822614 0.155516821 0.076451606]
$t^T$ = [ 2.137008627 1.137645489 3.935456068 1.996214262] for PSO
$h^T$ = [0.765382127 0.153215367 0.077231119]
$t^T$ = [2.176933106 1.205994222 4.010059489 2.058612345] for GA and
$h^T$ = [0.76918 0.15386 0.07672]
$t^T$ = [2.15839 1.15415 3.99853 2.09696] for AGA.

The linear filter of memory length of eight has selected for compensating memory effect of power amplifier model. Then, solving expression (7) with the help of estimated Wiener model's linear filter coefficient, the resulting linear filter coefficients for each case are given as

$h^T$ = [ 1.285640173 −0.257049189 −0.074970543 0.040254684 −0.000679669 −0.003820711 0.000830712 0.000209443] for PSO
$h^T$ = [ 1.306536911 −0.261544561 −0.079480117 0.042301686 −0.000448051 −0.004178773 0.000881724 0.000245156] for GA
and
$h^T$ = [1.300248917 −0.259939966 −0.078005391 0.041577799 −0.000514716 −0.004053171 0.000861742 0.000232875] for AGA.

The constellation diagrams of output signal from the combined pre-distorter using PSO, GA, and AGA algorithms combined with Wiener power amplifier model are shown in Figs. 3, 4, and 5 for IBO = 5 dB ('$x$' represents the output $y(k)$ and '$o$' represents the input 64-QAM signal $x(k)$).

From Figs. 3, 4, and 5, it can be seen that designed pre-distorters almost completely cancel out the nonlinear distortions and memory effects caused by the Wiener memory high-power amplifier model. Compared to PSO and GA, the pre-distorter designed using AGA has produced better results.

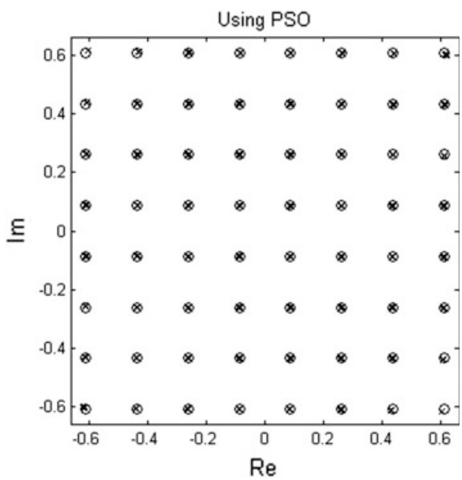


**Fig. 3** Output with pre-distorter using GA

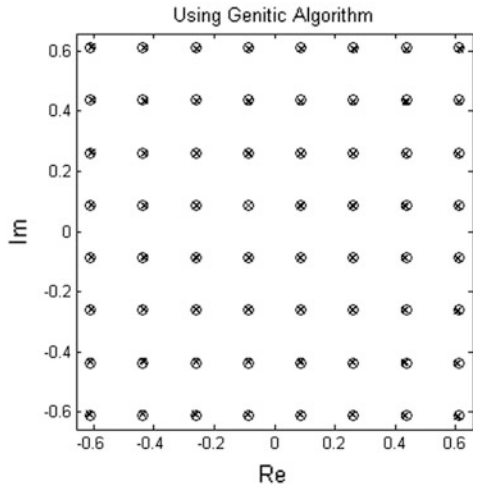


**Fig. 4** Output with pre-distorter using PSO

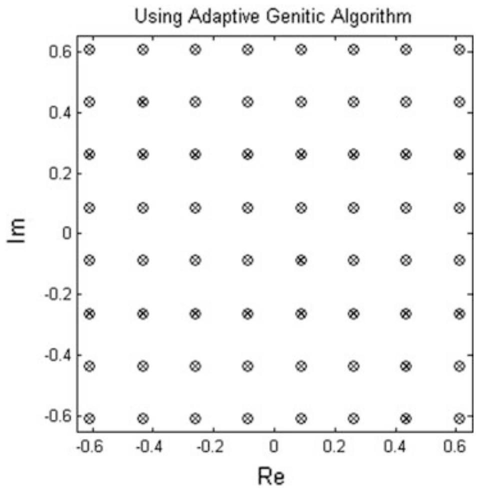


**Fig. 5** Output with pre-distorter using AGA

The performance of the designed pre-distorters was evaluated using the following mean-square error metric given in Eq. (8),

$$\mathrm{MSE} = 10\,\log_{10}\left(\frac{1}{K_{\text{total}}}\sum_{k=1}^{K_{\text{total}}}|x(k) - y(k)|^2\right) \tag{8}$$

where $K_{\text{total}}$ represents the total number of the test data, $x(k)$ was the input signal, and $y(k)$ was the output from the combined pre-distorter and memory high-power amplifier system. For calculating the effectiveness of pre-distorter, $K_{\text{total}}$ = 20,000

**Table 1** MSC values for different IBO values

| IBO | Without PD | PSO | GA | AGA |
|---|---|---|---|---|
| 1 | −0.88 | −18.6229 | −18.24353093 | −19.1624 |
| 2 | −2.20 | −23.7221 | −23.47215939 | −25.1326 |
| 3 | −3.577 | −29.2669 | −30.40934644 | −34.0816 |
| 4 | −4.993 | −33.0066 | −39.62186106 | −51.1595 |
| 5 | −6.427 | −35.4421 | −44.51344478 | −54.6613 |
| 6 | −7.85 | −37.9127 | −46.86382147 | −57.8648 |
| 7 | −9.23 | −40.3647 | −48.1744839 | −60.9684 |
| 8 | −10.54 | −42.7472 | −49.2292658 | −64.0139 |
| 9 | −11.77 | −45.0111 | −50.25339467 | −67.0112 |
| 10 | −12.91 | −47.1135 | −51.28417344 | −69.9547 |
| 11 | −13.98 | −49.0264 | −52.31811731 | −72.8268 |
| 12 | −14.98 | −50.7429 | −53.34854158 | −75.5979 |
| 13 | −15.95 | −52.2771 | −54.37218999 | −78.2279 |
| 14 | −16.91 | −53.6579 | −55.38871141 | −80.6707 |
| 15 | −17.85 | −54.9196 | −56.39920396 | −82.8851 |
| 16 | −18.78 | −56.0944 | −57.40518485 | −84.8483 |

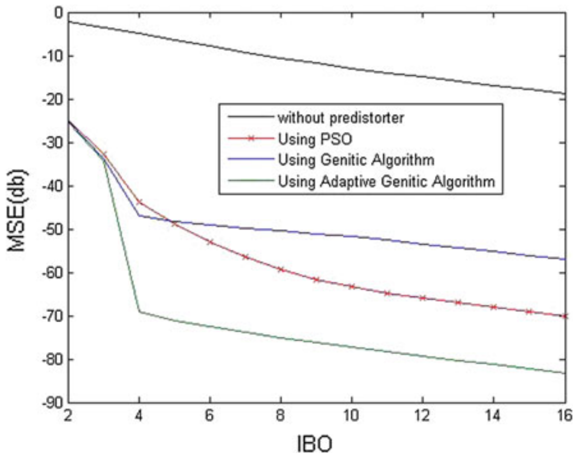


**Fig. 6** MSE versus IBO plot

samples of normalized 64 QAM data were allowed to pass through the combination of pre-distorter and Wiener power amplifier.

The mean-square error metric (MSE) was computed for each pre-distorters by noting input and output data. The obtained MSE for the pre-distorters is shown in Table 1 as a function of IBO.

Figure 6 depicts the MSE versus IBO plot for pre-distorters designed using corresponding estimated parameter vectors, where Wiener power amplifier is implemented using $h^{\mathrm{T}} = [0.7692\ 0.1538\ 0.0769]$ and $t^{\mathrm{T}} = [2.1587\ 1.15\ 4.0\ 2.1]$.

From Fig. 6 and Table 1, it is clear that pre-distorters designed with AGA-based identification method have greater reduction in MSE value than pre-distorter designed using PSO algorithm at lower IBO values. Hence, pre-distorter designed using AGA can be considered as the best one that provides good linearization.

## 4 Conclusion

The power amplifiers have steadily surfaced as inevitable modules in the communication systems. In this regard, the HPAs have brilliantly played their role and are offered a red carpet welcome in the burgeoning gamut of applications, especially in the fascinating world of the wireless communications. However, the HPAs are habitually deformed and exhibit a tendency to generate the nonlinear outputs, thereby miserably failing to attain the saturation level. In the innovative technique, the Wiener HPA technique is employed to devise the high-power amplifier and the authentic constraint vector has to be adapted here. The optimization process is carried out by means of the adaptive genetic algorithm (AGA). Thereafter, the optimized Wiener HPA is employed to devise the pre-distorter. The innovative technique is performed in the working platform of the MATLAB and the efficiency in execution is assessed and contrasted with that of the GA and PSO to illustrate the incredible efficiency of the epoch-making technique.

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