



SSA optimized digital pre-distorter for compensating non-linear distortion in high power amplifier

Mridula Malhotra¹ · Amandeep Singh Sappal¹

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Abstract

We applied the stochastic salp swarm algorithm (SSA) to design high power amplifier (PA) and digital pre-distorter (DPD) using generalized memory polynomial model. This algorithm has high exploitation and convergence speed to solve the non-linear coefficient of memory polynomial. We considered a single carrier WCDMA input for the static non-linearity of the memory based high power amplifier. Various simulations have been conducted to validate the performance of SSA over PA and DPD using different memory depths and degrees combinations which demonstrates that the proposed approach is an effective solution for linearity of high generation wideband transmitters. The performance of SSA is compared with particle swarm optimization and shows the superiority of SSA in terms of lower adjacent channel power ratio, error vector magnitude, normalized mean square error and modeling error. The implementation of SSA on PA and DPD has been done separately and then cascaded to generate a resultant linear output.

Keywords Adjacent channel power ratio · Digital pre-distorter · Error vector magnitude · Particle swarm optimization · Power amplifier · Salp swarm algorithm

1 Introduction

An RF power amplifier is an important part of wireless communication system. With the advent of modern wireless system, the use of large envelope signals are employed such as wideband code division multiple access (WCDMA), long term evolution (LTE) and Worldwide Interoperability for Microwave Access (WiMAX). To transmit these signals, high power efficient power amplifiers are required. But these PA suffers from high non-linearity [1]. High non-linearity is proportional to high peak to average power ratio. The non-linearity of PA can be defined by various models, e.g. Volterra model and its prone forms, memory polynomial (MP) model and its variants [2].

Many linearization techniques have been reported in literature such as envelope feedback, feed-forward and digital pre-distortion [1]. Out of these alternatives, the most promising solution for nonlinearity that can be employed is called digital pre-distorter, a non-linear device in cascade with PA

to remove non-linearity while maintaining power efficiency. Several forms of DPD have been proposed in the literature to meet the spectral requirements of communication system [3–9].

A pre-distorter model with left handed transmission line time delay was proposed in [3] which are applied for the cancellation of AM/PM distortion. A least square method was applied to identify the non-linear coefficient of PA [4]. In [5], the DPD system reduces the ACPR after bypassing the crest factor reduction block. The spline cross-term model of volterra series proposed in [6], reduces the pre-distorter system complexity without compromising the performance. A black box approach for DPD behavioral modeling was discussed in [7], to reduce the nonlinearity. In [8], the design authenticates the efficacy of the innovative pre-distorter for narrow bandwidth used in the 5G mobile communication generation. A fast and easy to implement DPD algorithm based on the feedback pre-distortion technique combined with the Complex memory polynomial structure was proposed in [9]. In [10], a generalized memory polynomial model was employed to wideband signal providing lower spectral regrowth. Thus, the improvement scope includes the variants of non-linearity equation and the optimized adaptive

✉ Mridula Malhotra
er.mridula@gmail.com

¹ ECE Department, Punjabi University, Patiala, PB, India

algorithm implementation upon PA and DPD to efficiently identify the non-linear coefficients.

In literature, various mathematical models have been used to define the PA non-linearity [2]. In this paper, the memory polynomial model has been used which is a special case of a generalized Hammerstein model. This paper model the power amplifier using salp swarm algorithm (PA-SSA) and further model the digital pre-distorter using salp swarm algorithm (DPD-SSA). Various sets of memory depth and degree of memory polynomial model have been used to validate the proposed solution. Lastly, the proposed model is compared with the traditional PSO algorithm on the PA and DPD. The rest of the paper is divided into following sections. Section 2 presents the related work upon the adaptive optimization algorithm used for PA and DPD. The modeling of PA and DPD has been discussed in Sect. 3. Performance Metrics of Power Amplifier are discussed in Sect. 4. PSO and SSA algorithms are briefly elaborated in Sects. 5 and 6, respectively. Section 7 includes the simulation study and discussion. Section 8 finishes this contribution by summarizing the conclusions.

2 Related works

In this section, the related work upon adaptive optimization algorithms has been discussed. The optimization algorithm is meant to reduce the system complexity without compensating the performance. In [11], the optimization of least square method was implemented by under-sampling technique and higher bandwidth training signal. The scope also includes nature inspired meta-heuristic swarm algorithms [12] to solve real life non-linear problem. In the meta-heuristic methods, the real time optimization problems are taken as a black box. Therefore, the trouble of finding derivative of the research space is removed. A meta-heuristic genetic algorithm was implemented in [13] to extract coefficients of the Wiener model to obtain better performance than the conventional pre-distorters. In [14], PSO was used to identify non-linear parameters and results into low memory cost and insignificant memory-units. The PSO was used in [15] to achieve a linearized PA, competent to efficiently recompense higher power aided efficiency and gain. A PSO with embedded ability of model-size estimation was proposed in [16]. In [17], hill-climbing (HC) heuristic algorithm with low execution time was used for memory polynomial model of PA, to provide the best tradeoff between modeling accuracy and complexity.

In [18, 19], the authors implemented the hybrid of PSO to reduce the system complexity. In [18], the modified PSO was used by finding the best position as per probability and combined with modified artificial bee colony algorithm which was used to find the best fitness of the signal. This hybrid

algorithm was used upon weiner model of PA to compensate non-linear distortions. In [19], a convergence solution was provided by modified PSO, where one particle position was set to the model parameter vector, rather being random. The remaining particles positions were randomly initialized. The initial velocity was taken zero to reduce the complexity.

Although, the researchers have put efforts in the improvement of power efficiency and linearization of power amplifier using various optimization methods, but the scope of improvement always exists. This paper proposed a novel optimization to the power amplifier using SSA and contributes in the field of power amplifier linearization.

3 Modeling of power amplifier and digital pre-distorter

The ultimate aim of designing appropriate pre-distorter is to compensate the distortions and ensure linear amplification of the signal to be transmitted. Conceptually, pre-distortion consists in applying a non-linear function prior of the PA; reciprocator to that of the amplifier to be linearized. Thus to design a DPD, the non-linearity of PA should be identified. The identified non-linear coefficient of PA are used to generate the coefficients of DPD in such a way that the cascade of both gives a resultant linear characteristics [1]. The dynamic non-linear system can be fully modeled by volterra series, but it is difficult to manipulate due to its complexity. However, a reduced form of volterra series, called memory polynomial model can be implemented. This model has reduced number of coefficients, while maintaining satisfactory accuracy. This model also considers the memory effects of PA [1]. The generalized memory polynomial model can be defined as [20]

$$y(n) = \sum_{m=0}^M \sum_{k=1}^K c_{2k-1,m} |x(n-m)|^{2(k-1)} x(n-m), \quad (1)$$

where $x(n)$ and $y(n)$ are the input and output complex base band signal, $c_{k,m}$ are complex valued coefficient parameter and M and K are the memory length and the non-linearity order of polynomial. The non-linear output of PA can be represented as

$$y(n) = \phi_{MP}(n) \cdot A, \quad (2)$$

where $\phi_{MP}(n)$ is a complex vector built using the baseband complex input signal samples $x(n-m)$ according to the model's basis functions set, and A is the vector containing the model coefficients.

The unknown complex coefficient matrix of the model can be written as

$$A = X^{-1} \cdot y, \quad (3)$$

where X and y are known input and output matrices. Note here we consider only the odd harmonics because the even harmonics are far away from the center frequency.

Calculation of the model coefficients A requires a non-linear system identification technique such that,

$$Y \rightarrow AX \text{ or } AX - Y \rightarrow 0. \tag{4}$$

The least square estimation criteria have been used to find the model coefficients as follows:

The error vector $e = AX - Y$ or, its square, approaches zero (minima)

$$\min_A ||e^T e|| = \min_A ||\{(AX - Y)^T(AX - Y)\}, \tag{5}$$

$$= \min_A (A^T X^T X A - 2Y^T X A + Y^T Y). \tag{6}$$

Thus, the cost function or fitness function used in context of the system design is as follows.

$$(A^T X^T X A - 2Y^T X A + Y^T Y). \tag{7}$$

Minimization of fitness function is required for optimization of PA and DPD.

4 Performance metrics of power amplifier

In order to evaluate the performance of given models, the metrics used are normalized mean-square error (NMSE), adjacent channel power ratio (ACPR) and error vector magnitude. NMSE and ACPR are defined by (8) and (9), respectively [21],

$$NMSE \text{ (dB)} = 10 \log_{10} \frac{\int \varphi_{err}(f)df}{\int \varphi_{meas}(f)df}, \tag{8}$$

where $\varphi_{err}(f) = \varphi_{meas}(f) - \varphi_{modeled}(f)$ is the error signal's power spectrum and $\varphi_{meas}(f)$ is the measured signal power spectrum

$$ACPR \text{ (dB)} = 10 \log_{10} \frac{\int_{adjchn} \varphi_{meas}(f)df}{\int_{mainchn} \varphi_{meas}(f)df}, \tag{9}$$

The error vector magnitude (EVM) is used to analyze the in band distortion. EVM is a measure of how accurately the symbols are transmitted within its constellation. The difference between the received vector and actual signal vector is called the error vector and magnitude of error vector is EVM defined as [22]:

$$EVM \text{ (dB)} = 10 \log_{10} \sqrt{\frac{E[\varphi_{err}^2]}{\alpha E[\varphi_{ref}^2]}}, \tag{10}$$

where α is the scaling factor and φ_{ref} is reference signal.

The cost function or fitness function for the optimization of PA and DPD is NMSE. The minimum the value of NMSE, better is the performance and accuracy.

5 Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization method [23] proposed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of bird flocking. The target position, say, a cornfield has always a dynamic force for attracting all birds. The position of each particle is evaluated by calculating its distance from the target. Considering a swarm size S for a population space of dimension D , the position of each particle i is represented by a vector X in multi-dimensional space. v_{id} is the initial velocity of the particle, $\omega(t)$ is the current weight of the particle. When these particles move in search space, then each particle position is updated to attain the best position called personal best represented by X_{id}^{best} and $gbest_d^{t-1}$ is the global best position of the particle at the end of iterations as shown in Fig. 1. After every iteration, the algorithm renews the velocity v_{id}^t and current position X_{id}^t of the D th dimension of the i th particle by the following equations [23]:

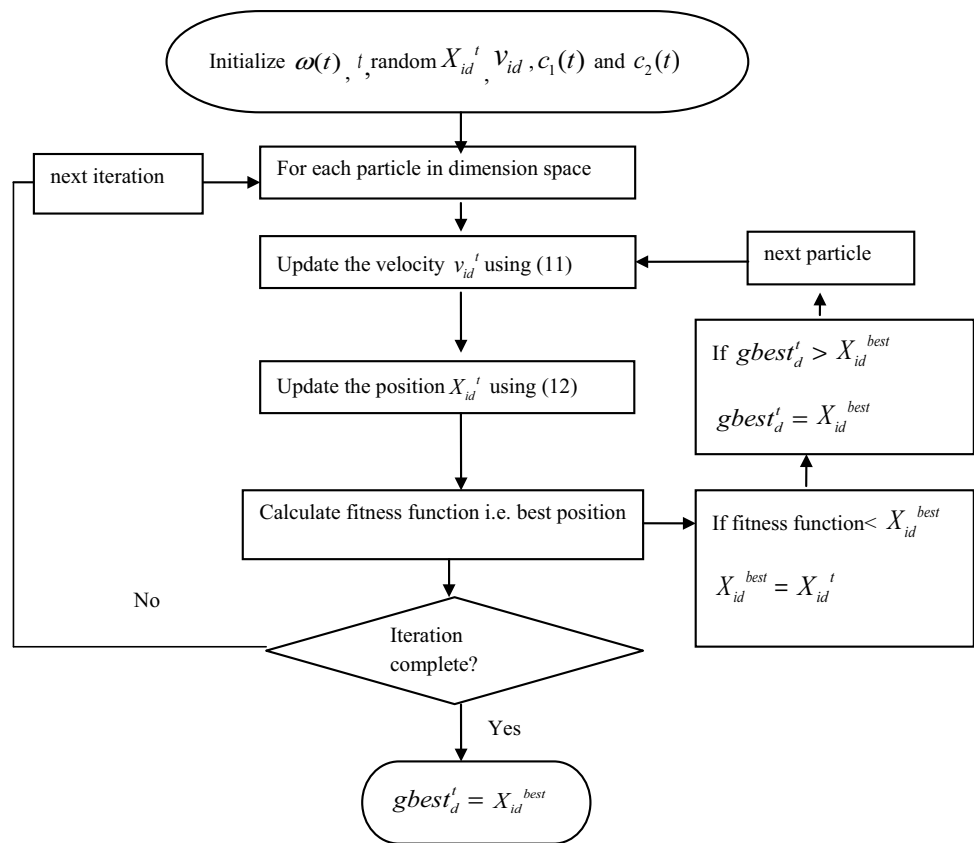
$$v_{id}^t = \omega(t) * v_{id}^{t-1} + \alpha * c_1(t) * rand1_{id}^t * (X_{id}^{best} - X_{id}^{t-1}) + \beta * c_2(t) * (1 - rand1_{id}^t) * (gbest_d^{t-1} - X_{id}^{t-1}). \tag{11}$$

If $v_{id}^t > v_{id}^{d,max}$ or $v_{id}^t < v_{id}^{d,min}$ then $v_{id}^t = \cup(v_{id}^{d,max}, v_{id}^{d,min})$.

$$X_{id}^t = rand2_{id}^t * X_{id}^{t-1} + (1 - rand2_{id}^t) * X_{id}^t. \tag{12}$$

where $c_1(t)$ and $c_2(t)$ = time-varying acceleration coefficients and $\omega(t)$ = time-varying inertia weight, $rand1$ and $rand2$ are uniform random numbers between 0 and 1, having different values in different dimension, t is the current generation number. The speed of convergence β varies between [0, 1]. And $\alpha = \alpha_0 * \gamma$ where, α_0 is the initial value of the randomness parameter [0.5 < α_0 < 1] where γ is the control parameter [0 < γ < 1]. The velocity and position are renewed until the number of iteration is completed, usually when there is no further update of best fitness value. The flowchart of PSO is shown in Fig. 1.

Fig. 1 Flowchart of PSO



6 Salp swarm algorithm (SSA)

Mirjalili [24] introduces a bio inspired salp swarm algorithm in 2017 for the engineering design problem. Compared to other swarm optimization algorithm, SSA benefits from high exploitation and convergence speed [24].

In this algorithm, the salps move for the search of target. The first member of salp chain is the leader and the rest of salps chains are followers. As the name of these salps implies, the leader guides the followers follow each other for the food source F. The position of salps are defined in an n-dimensional search space D and are reserved in a two-dimensional matrix called X and the position of the leader salp in the jth dimension is defined as [24]

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & c_3 \geq 0 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & c_3 < 0 \end{cases} \quad (13)$$

where F_j is the position of the food source, ub_j and lb_j indicates the upper and lower bound of jth dimension, c_1 , c_2 and c_3 are the random coefficients. The coefficient c_1 balances exploration and exploitation and is defined as follows:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2}, \quad (14)$$

where l and L are the current and maximum number of iterations. The followers with $i \geq 2$ updates the position as

$$x_j^i = \frac{1}{2}at^2 + v_0t, \quad (15)$$

where t is iteration time, v_0 is the initial speed, and $a = \frac{v_{final}}{v_0}$, where $v = \frac{x-x_0}{t}$. At $t = 1$ and $v_0 = 0$, the equation can be rewritten as follows:

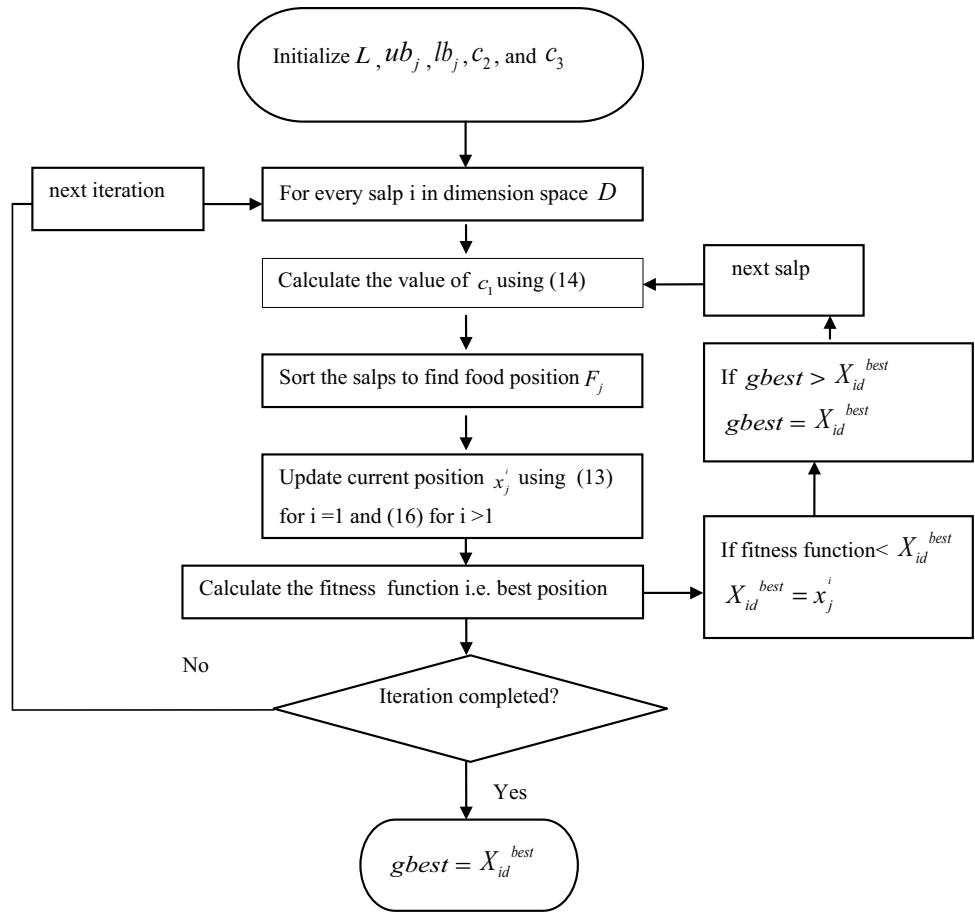
$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}). \quad (16)$$

The global best position, $gbest$ is calculated at the end of iterations as shown in Fig. 2.

7 Simulation study and discussion

We applied a single carrier WCDMA signal to the static non-linear memory based high power amplifier. In simulation based optimization approach, the PSO and SSA optimization algorithms are implemented using MATLAB. The RF WCDMA signal is generated using RF tone generator of system vue software. The non-linear coefficients of the PA and DPD model were identified using the SSA and PSO algorithms as stated below.

Fig. 2 Flowchart of SSA

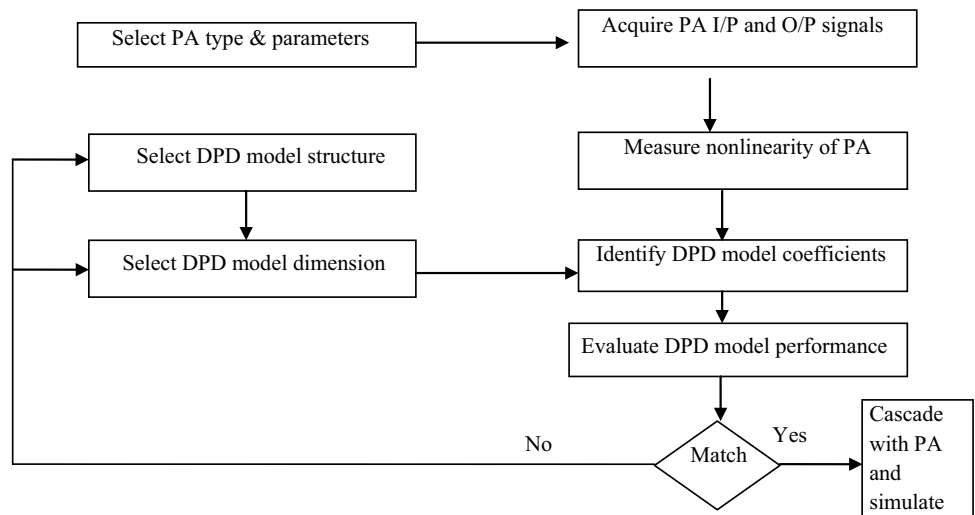


$$A = \begin{pmatrix} gbest_d^t \text{ for PSO} \\ gbest \text{ for SSA} \end{pmatrix} \quad (17)$$

The methodology followed for simulation is depicted in Fig. 3. We considered 100 iterations for the swarm size of 100. The performance of PSO and SSA are evaluated to

fit for a minimum value of the non-linear coefficient. The coefficient vector set in (3) has been updated by recursive iterative method or the best optimal solution found by the algorithm as discussed in Sects. 5 and 6. The algorithms are applied on PA as well as upon DPD using matlab and the performance has been verified on the basis of power spectrum, amplitude and phase characteristics as shown in

Fig. 3 Flow chart of digital pre-distortion processes



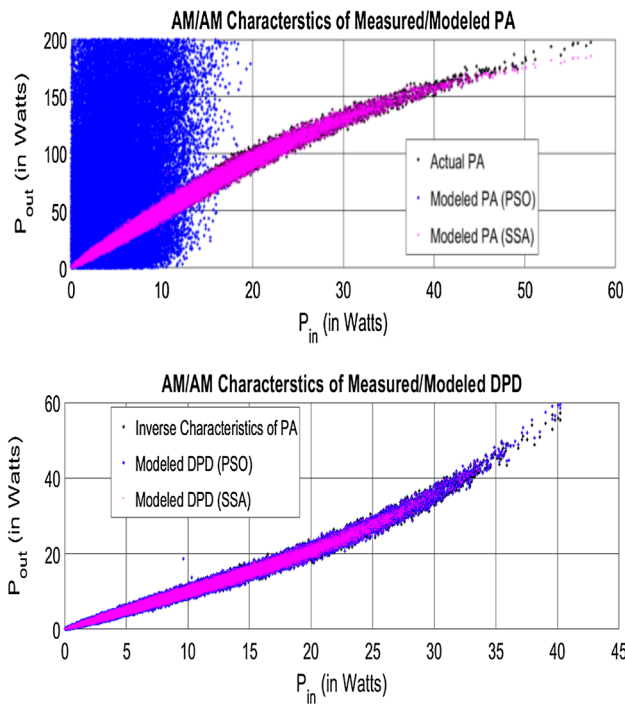


Fig. 4 AM-AM characteristics of a PA and b DPD

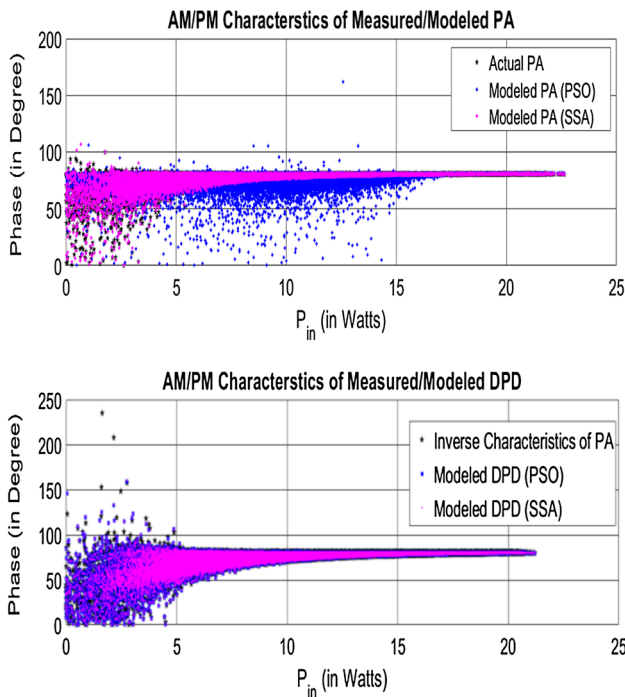


Fig. 5 AM-PM characteristics of a PA and b DPD

Figs. 4, 5, 6 and 7. The simulation graphs are taken for training length 100000, memory 5 and degree 5. The degrees

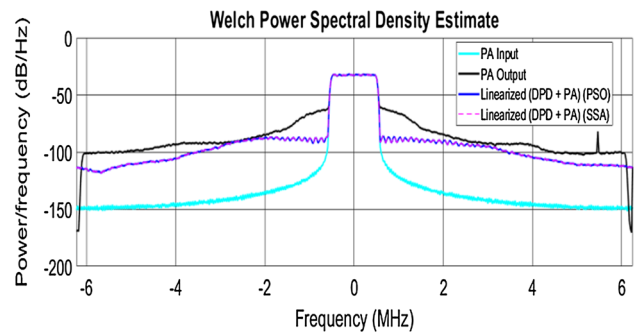


Fig. 6 Spectrum of linearized DPD+PA using PSO and SSA algorithm

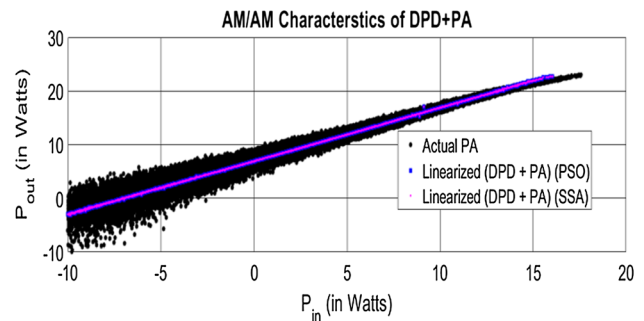


Fig. 7 Linearized AM-AM characteristics using PSO and SSA algorithm

and memory depths are varied to evaluate the overall performance as shown in Fig. 8 and Table 1.

The PSO performance is shown by blue line and SSA performance is depicted using pink line. The actual PA characteristics without algorithm have been shown using black color. The AM-AM characteristics of PA and DPD implanted with PSO and SSA are compared in Fig. 4.

The PA shows better characteristics using SSA, but has high dispersion using PSO. The DPD model using SSA has also better amplitude characteristics as compared to DPD using PSO.

The AM-PM characteristics of PA and DPD, modeled using PSO and SSA are illustrated in Fig. 5. The phase characteristics are more deviated using PSO modeling for PA as well as DPD. This indicates better accuracy of SSA as compared to PSO. The frequency spectrum of DPD+PA is illustrated in Fig. 6. It shows lower spectral regrowth at the output while using SSA and PSO algorithms as compared to actual PA output without adaptive algorithm. The AM-AM characteristics of cascaded linearized DPD+PA using PSO and SSA algorithms has been illustrated in Fig. 7 which also shows the low dispersed amplitude characteristics and accuracy of PSO and SSA optimized algorithms as compared to PA output without

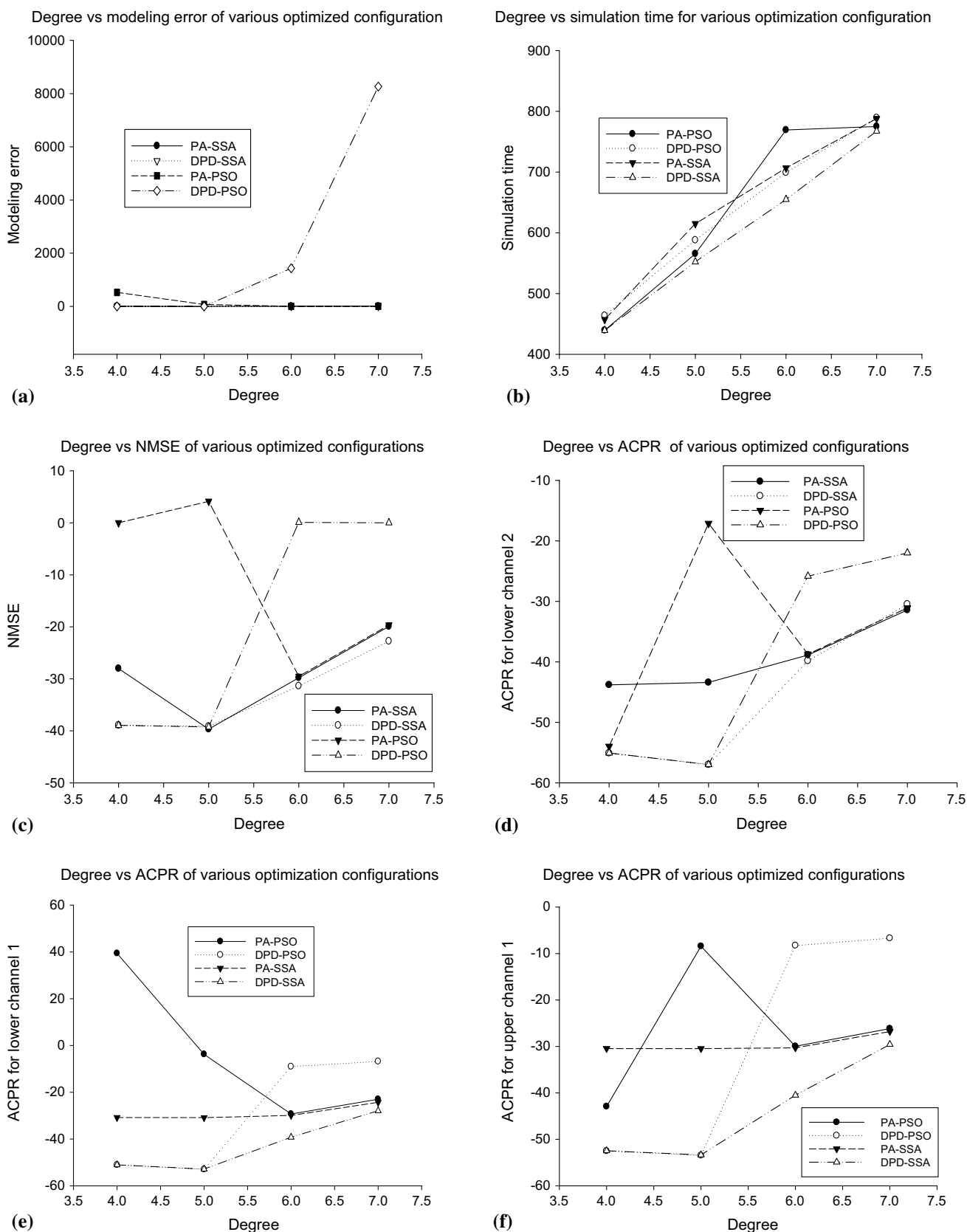


Fig. 8 Parametric analysis of various optimized configuration at M=5

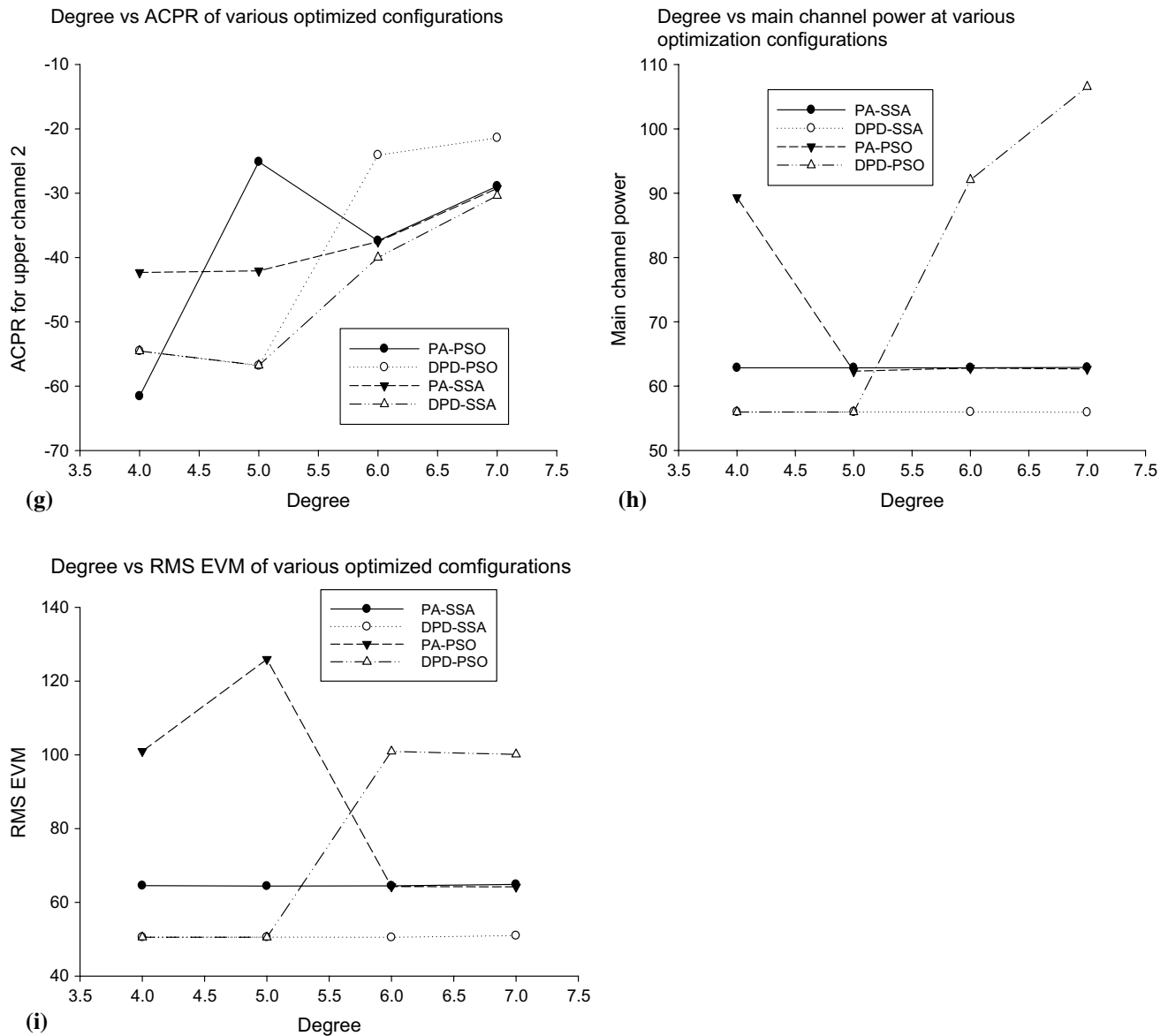


Fig. 8 (continued)

optimization. Also the linearity is maintained beyond the saturation point.

Various simulations are conducted at different degree and memory depth combinations and briefly presented the parametric performance in Fig. 8 and Table 1.

It has been observed that the modeling error is quite low using SSA, even for higher degrees as compared to that of PSO implementation. For degree 7, as shown in Fig. 8a, the modeling error is $8.2659e+03$ for DPD-PSO while it is 1.1557 for DPD-SSA.

Figure 8b depicts that the simulation time increases with increase in the degree and memory. Comparing both algorithms, SSA shows lesser values of simulation time

for lower memory depth and degrees for example, at $M=5$ and $K=7$ it is 775.0986 and 789.4345 for PA-PSO and DPD-PSO, while 788.2425 and 767.4655 for PA-SSA and DPD-SSA, respectively, as shown in Table 1.

The SSA implementation has overall low NMSE for higher degrees and memory depths as illustrated in Fig. 8c. From Table 1, the values observed are -19.6410 and 0.0147 for PA-PSO and DPD-PSO, while -19.9073 and -22.7473 for PA-SSA and DPD-SSA, respectively.

The offset value of the adjacent channels are taken at -10 , -5 , 5 and 10 MHz for lower 2, lower 1, upper 1 and upper 2 adjacent channels, respectively. The ACPR of

Table 1 Comparison of SSA and PSO performance for different parameters

Optimization	M	K	Error	Time (s)	NMSE (dB)	ACPR (dB)	Main channel power (dB)	RMS EVM (dB)
PA-PSO	5	5	71.0445	565.4436	4.1431	[− 17.1089 − 3.7422 − 8.4191 − 25.1195]	62.3242	125.9530
DPD-PSO	5	5	0.1525	587.9363	− 39.2587	[− 56.9919 − 52.9697 − 53.4786 − 56.8300]	55.9729	50.5089
PA-SSA	5	5	0.3230	615.1942	− 39.6675	[− 43.4135 − 30.8715 − 30.4613 − 42.0417]	62.8456	64.4214
DPD-SSA	5	5	0.1556	552.2610	− 39.1548	[− 56.9888 − 52.8371 − 53.3509 − 56.7815]	55.9727	50.5601
PA-PSO	5	7	3.9877	775.0986	− 19.6410	[− 31.0822 − 22.9982 − 26.1515 28.8929]	62.6592	64.1816
DPD-PSO	5	7	8.2659e+03	789.4345	0.0147	[− 21.9728 − 6.7738 − 6.7018 − 21.3985]	106.5407	100.1464
PA-SSA	5	7	4.1228	788.2425	− 19.9073	[− 31.4169 − 24.3109 − 26.7817 29.2426]	62.8923	64.8801
DPD-SSA	5	7	1.1557	767.4655	− 22.7473	[− 30.4539 − 27.9190 − 29.5580 − 30.3702]	55.9230	50.9562

adjacent channels has been observed as lower in case of SSA implementation as shown in Fig. 8d–g.

The main channel power and root mean square EVM has the overall higher values using PSO, but using SSA, it shows insignificant EVM, even with increase in degree as shown in Fig. 8h, i. Note that all the simulations are performed at a training length of 100000 samples.

8 Conclusion

In this paper, a memory polynomial PA and DPD model optimized using salp swarm optimization has been proposed. This proposed approach was found to achieve good performance in terms of estimating accuracy while having reduced modeling error. The stochastic salp swarm algorithm implemented on PA and DPD results into a low RMS EVM, NMSE and ACPR values at higher degrees and memory depths.

The SSA modeled system provides higher main channel power. The performances of the proposed SSA based pre-distorter has been compared with those of the regular PSO

based pre-distorter and the results illustrate the superior ability of SSA modeled pre-distorter to reduce spectral regrowth and better linearization of high generation wideband power amplifiers.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Mridula Malhotra received her B.Tech. degree in electronics and communication engineering from the Jind Institute of engineering and communication, Kurukshetra University, an M.Tech. in VLSI Design from the National institute of technology, Kurukshetra. She has worked as an assistant professor in lovely professional university for 6 years and currently pursuing Ph.D. degree in electronics and communication engineering from the Punjabi University. Her current research interests include wireless telecommunication, signal processing and VLSI design.



Amandeep Singh Sappal has passed his B.E. in Electronics and Electrical Communication from Punjab University, Chandigarh in 1995. He has done his Ph.D. from Faculty of Engineering and Technology, Punjabi university, Patiala in 2011. He has more than 16 years of teaching and research experience. He has more than 60 research publications at his credit. He has delivered expert talks in various universities of north India. He has guided more than 20 M. Tech. thesis and 4 Ph.D. candidates are working under him. He is a reviewer of various prestigious international journals. He is also a member of various technical societies. His main interests are Design of Wireless Communication Systems using Embedded Systems, Digital Signal Processing, Optical and Wireless Communication. He is presently working as assistant professor in Department of Electronics and Communication Engineering, Punjabi University, Patiala (India).