

A modified particle swarm optimization algorithm and its application to the multiobjective FET modeling problem

Ufuk ÖZKAYA*, Filiz GÜNEŞ

Department of Electronics and Communication Engineering, Yıldız Technical University,
Beşiktaş, 34349 İstanbul-TURKEY
e-mails: {uozkaya, gunes}@yildiz.edu.tr

Received: 09.02.2011

Abstract

This paper introduces a modified particle swarm algorithm to handle multiobjective optimization problems. In multiobjective PSO algorithms, the determination of Pareto optimal solutions depends directly on the strategy of assigning a best local guide to each particle. In this work, the PSO algorithm is modified to assign a best local guide to each particle by using minimum angular distance information. This algorithm is implemented to determine field-effect transistor (FET) model elements subject to the Pareto domination between the scattering parameters and operation bandwidth. Furthermore, the results are compared with those obtained by the nondominated sorting genetic algorithm-II. FET models are also built for the 3 points sampled from the different locations of the Pareto front, and a discussion is presented for the Pareto relation between the scattering parameter performances and the operation bandwidth for each model.

Key Words: FET modeling, multiobjective optimization, pareto optimal analysis, particle swarm optimization

1. Introduction

During the past decades, population-based evolutionary computation methods have been investigated and implemented to various optimization problems by utilizing the cooperation and competition among the potential solutions. In single-objective optimization problems, potential solutions aim to find an optimum solution vector including optimized parameters by minimizing/maximizing the objective function. However, many real-world problems consist of multiple objectives that conflict with each other; this is called the multiobjective optimization problem. In such a case, all of the conflicting objectives are transferred to a single objective function. In order to balance the conflicting objectives, additional approaches, such as weighted sums or fuzzy membership functions, are used [1]. An alternate way is to find, instead of a singular solution vector, a set of solutions

*Corresponding author: Department of Electronics and Communication Engineering, Yıldız Technical University, Beşiktaş, 34349 İstanbul-TURKEY

including nondominated solutions of conflicting objectives; this is called the Pareto optimal solution. Therefore, stochastic optimization methods have to be reconfigured in accordance with the Pareto optimal concept so as to overcome multiobjective optimization problems.

The particle swarm optimization (PSO) algorithm is an evolutionary algorithm capable of solving difficult multidimensional optimization problems in various fields. Since its introduction in 1995 by Kennedy and Eberhart [2], PSO has gained increasing popularity with its superior optimization performance. In PSO, particles keep searching to find the optimum solution based on the best experience of the swarm (global best, or gbest) by using their past experiences (personal best, or pbest) until the expectation is met. The guidance of the global best particle is essential for convergence to the minima/maxima. However, because of the presence of a set of nondominated solutions, the guide selection procedure is redefined in multiobjective particle swarm optimization algorithms. A new term, "best local guide," is defined for each particle for the determination of Pareto optimal solutions of conflicting objectives. In [3,4], new methods were proposed in order to find the best local guide for each particle of the swarm.

In this work, the PSO algorithm is modified to assign a best local guide to each particle by determining its minimum angular distance to the current Pareto front in the polar coordinate system. The current Pareto front is built by the particles whose current positions satisfy the Pareto domination relation in the objective space. The modified PSO algorithm is implemented to a multiobjective microwave field-effect transistor (FET) modeling problem. The problem consists of the determination of 9 unknown FET model elements with technological limitations for optimum scattering parameters and operation bandwidth. The resulting Pareto optimal solutions are compared with those obtained by the nondominated sorting genetic algorithm-II (NSGA-II).

In the following section, the multiobjective optimization concept will be explained. The modified PSO algorithm and the strategy for assigning the best local guide are addressed in Section 3. In Section 4, the FET modeling problem will be defined as a multiobjective optimization problem. In Section 5, the attributes of the optimization procedure will be given and the results and comparison will be discussed. The work will be concluded in the final section.

2. Multiobjective optimization

Multiobjective optimization is the process of the simultaneous minimization or maximization of m objective functions $\vec{f}(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x}))$ with respect to n decision variables $\vec{x} = (x_1, x_2, x_3, \dots, x_n)$ subject to the given constraints in the decision space X . The Pareto domination relation between these solution vectors can be defined as follows:

- $\vec{x}_1 \prec \vec{x}_2$ (\vec{x}_1 weakly dominates \vec{x}_2) if and only if $f_i(\vec{x}_1) \leq f_i(\vec{x}_2)$ for all $i \in \{1, 2, \dots, m\}$,
- $\vec{x}_1 \prec \vec{x}_2$ (\vec{x}_1 dominates \vec{x}_2) if and only if $\vec{x}_1 \prec \vec{x}_2$ and $f_j(\vec{x}_1) < f_j(\vec{x}_2)$ for at least one $j \in \{1, 2, \dots, m\}$, and
- $\vec{x}_1 \sim \vec{x}_2$ (\vec{x}_1 is indifferent to \vec{x}_2) if and only if \vec{x}_1 does not dominate \vec{x}_2 and \vec{x}_2 does not dominate \vec{x}_1 .

In the case where \vec{x}_1 and \vec{x}_2 dominate other solution vectors but not each other, they are deemed mutually optimal solutions and are referred to as the Pareto optimal. The set of Pareto optimal solutions reflects the trade-off surfaces between the different objectives. This set of Pareto optimal solutions is referred to as the Pareto front.

3. Modified PSO algorithm

PSO is a population-based optimization method and can be formulized as follows. For an N- dimensional problem, the position and velocity can be specified by $M \times N$ matrices, where M is the number of particles in the swarm. Each row of the position matrix represents a possible solution to the optimization problem, and the i th particle of the swarm is represented by N-dimensional vector $X_i = [x_{i1}, x_{i2}, \dots, x_{iN}]^T$. Similarly, the velocity of the i th particle is represented by N-dimensional vector $V_i = [v_{i1}, v_{i2}, \dots, v_{iN}]^T$. Each particle has a memory of the best position of the search space that has ever been obtained at each iteration, and the personal best performance of the i th particle is defined as $pbest_i = [pbest_{i1}, pbest_{i2}, \dots, pbest_{iN}]^T$. The global best position vector defines the position in the solution space at which the lowest cost value was achieved by all particles, defined by $gbest = [gbest_1, gbest_2, \dots, gbest_N]^T$. The velocity of each particle depends on the distance of its current position from that resulting in lower cost values. To update the velocity matrix at each iteration, every particle should know its personal best and the global best position vectors. Thus, all of the information needed by the PSO algorithm is contained in X, V, pbest, and gbest. The core of the PSO algorithm is the method by which these matrices are updated in every iteration of the algorithm. In our work, the velocity matrix and the position matrix are updated according to the following equations.

$$v_i^t(n) = w^t * v_i^{t-1}(n) + c_1 * U_{i1}^t * (Pbest_i^t(n) - x_i^{t-1}(n)) + c_2 * U_{i2}^t * (Gbest^t(n) - x_i^{t-1}(n)) \quad (1)$$

$$x_i^t(n) = x_i^{t-1}(n) + v_i^t(n), \quad i = 1, \dots, M; \quad n = 1, \dots, N \quad (2)$$

Here, the superscripts t and t-1 refer to the time index of the current and the previous iterations, w is the inertia weight, c_1 and c_2 are the learning factors of the swarm, and U_{i1}^t and U_{i2}^t are 2 uniformly distributed random numbers in the interval [0,1] and are different for each of the n components of the particle's velocity vector.

In single-objective PSO algorithms, particles converge to the optimum solution with the guidance of the particle that has the best position. Because of the presence of a set of nondominated solutions in multiobjective optimization problems, each optimal solution on the Pareto front can guide the particles to change their position. Assigning a proper guide to each particle is a vital stage for the determination of Pareto optimal solutions.

In this work, the single-objective PSO algorithm is modified to overcome multiobjective optimization problems based on the Pareto domination concept. A new approach is proposed to assign a best local guide to each particle using minimum angular distance information. In Figure 1, the main steps of the modified PSO algorithm are given. These steps can be explained as follows.

Step 1: The dimension of the optimization problem, the lower and upper boundary values for each parameter to be optimized, conflicting objective functions, and the number of particles are defined.

Step 2: The position of the population is initialized randomly within the lower and upper values. The initial velocity values of the particles are set to zero and the initial personal best values are assigned from the initial position values of population. For each iteration, nondominated solutions are stored in the archive.

Step 3: Each particle in the population evaluates objective functions and is mapped into biobjective space. Each particle updates its personal best position by comparing the current and last values in biobjective space. After the evaluation of all particles, the current nondominated solutions are obtained and stored in the archive. The particles update their velocities and positions with the guidance of an assigned best local guide and by using their past experiences at each iteration. The strategy of assigning a best local guide to each particle can be explained as follows.

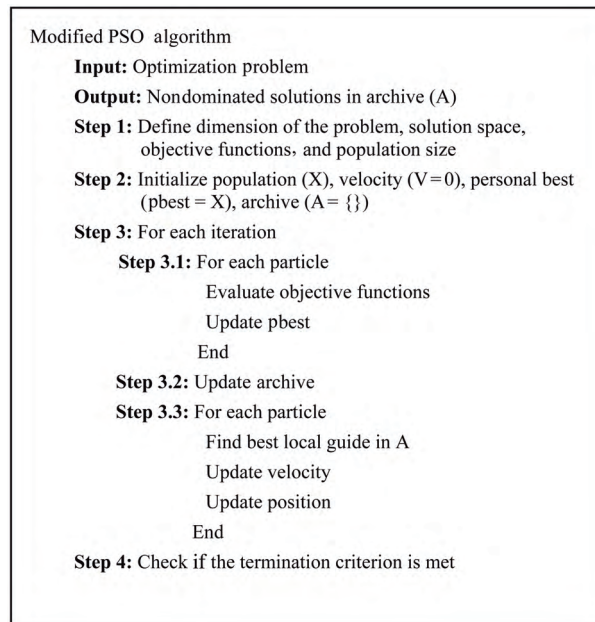


Figure 1. Main steps of modified PSO algorithm.

The nondominated solutions (stored in the archive) obtained in biobjective space are mapped from Cartesian coordinates into a polar coordinate system. Thus, each solution is defined in terms of the radius and polar angle. Let N be the number of optimal solutions stored in the archive. A_{ij} ($i = 1, \dots, N$ and $j = 1, 2$) denotes the values of the optimal solutions in biobjective space. The members of the archive are mapped into polar coordinates, as given below.

$$\begin{bmatrix} A_{11} & A_{12} \\ \vdots & \vdots \\ A_{N1} & A_{N2} \end{bmatrix} \Leftrightarrow \begin{bmatrix} r_1 & \theta_1 \\ \vdots & \vdots \\ r_N & \theta_N \end{bmatrix} \quad (3)$$

Similarly, the position of each particle in biobjective space is mapped and each particle has a radius and a polar angle value. Each particle then calculates the polar angle distance between the members of the archive.

The optimal solution with the minimum angular distance is assigned as the best local guide for each particle. Thus, particles in the population change their position toward the Pareto optimal solution, as shown in Figure 2. The position and velocity of each particle is updated by Eqs. (1) and (2), and the best local guide replaces gbest.

4. FET modeling as a multiobjective optimization problem

The conventional and complete FET model that is commonly available to designers is shown in Figure 3. The complete FET model consists of intrinsic parameters such as C_{gd} , C_{gs} , R_i , g_m , C_{ds} , and R_{ds} and extrinsic elements such as r_g , L_g , r_d , L_d , r_s , and L_s . The scattering parameters of the complete FET model in Figure 3 can be derived using their definitions, as follows [5,6].

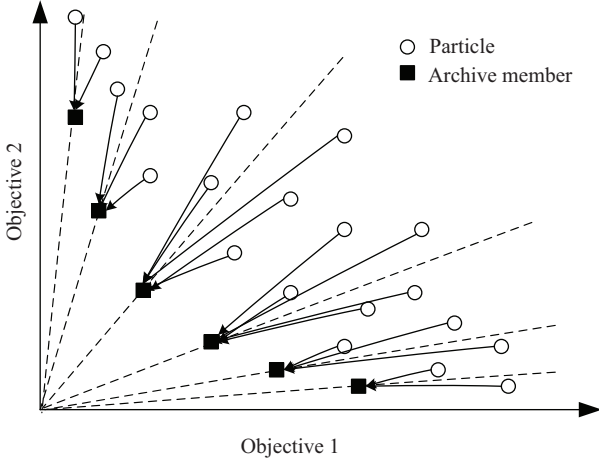


Figure 2. Best strategy for assigning local guide in modified PSO.

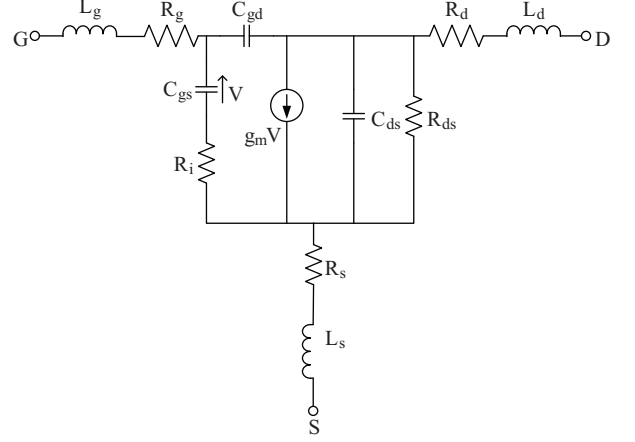


Figure 3. Complete FET model.

$$S_{11}(f) = \frac{1 + j2\pi f C_{gse}(R_{ie} - R_o)10^{-3}}{1 + j2\pi f C_{gse}(R_{ie} + R_o)10^{-3}} \quad (4)$$

$$S_{12}(f) = \frac{j2\pi f R_o C_{gd} 10^{-3}}{1 - (2\pi f R_o 10^{-3})^2 C_{gd} C_{gsw} + j2\pi f (2C_{gd} + C_{gsw}) R_o 10^{-3}} \quad (5)$$

$$S_{21}(f) = \frac{2R_{dso} g_m}{(1 + j2\pi f R_{io} C_{gse} 10^{-3}) \times (1 + j2\pi f R_{dso} C_{dse} 10^{-3})} \quad (6)$$

$$S_{22}(f) = \frac{(1 + j4\pi f C_{gd} R_o 10^{-3}) R_{dsh}}{1 + j2\pi f C_{gdh} (R_{dsh} + 2R_o) 10^{-3} - (2\pi f C_{gdh} 10^{-3})^2 R_{dsh} R_o} \quad (7)$$

Here, $R_o = 50 \Omega$ as the reference termination, and the other parameters, in terms of the model parameters, are as follows.

$$R_{dso} = R_o R_{dse} / (R_o + R_{dse}) \quad (8)$$

$$R_{io} = R_{ie} + R_o \quad (9)$$

$$R_{dsh} = R_d + R_s + R_{ds}(1 + g_m R_s) \quad (10)$$

$$C_{gdh} = C_{gd} \left(1 + R_o g_m + \frac{C_{ds}}{C_{gd}} \right) \quad (11)$$

$$C_{gsw} = R_o C_{gd} \left(g_m + \frac{1}{R_{ds}} \right) + C_{gs} \left(1 + \frac{R_o}{R_{ds}} \right) + C_{ds} \quad (12)$$

$$C_{gse} = C_{gs} + C_{gd}(1 - g_a) \quad (13)$$

$$C_{dse} = C_{ds} + C_{gd}(g_a - 1)/g_a \quad (14)$$

$$R_{ie} = R_i + R_s + R_g, \quad g_a = -g_m \frac{R_o R_{dse}}{R_o + R_{dse}} \quad (15)$$

$$R_{dse} = \frac{R_o + R_{ds}}{r_a + R_o}, \quad r_a = R_d + R_s(1 + g_m R_{ds}) \quad (16)$$

Here, f denotes discrete frequencies in the desired operation band. As clearly seen from Eqs. (4) through (16), the S-parameters are expressed in terms of FET model elements by neglecting parasitic inductances L_g , L_d , and L_s . For input and output terminations of 50Ω , the transducer power gain of the FET device is equal to:

$$G_T(f) = |S_{21}(f)|^2. \quad (17)$$

Generally, maximizing the transducer power gain is considered as the main design objective in FET modeling applications. FET modeling for the transducer power gain is very essential, but reflection and reverse transmission losses should also be taken into account in the design stage. Since the FET device is terminated with 50Ω , the input and output reflection losses are equal to S_{11} and S_{22} , respectively. Thus, minimizing the reflection losses and the reverse transmission (S_{12}) should be considered as important design objectives. Another design objective is to obtain an FET model ensuring these objectives in the maximum operation bandwidth. FET modeling subject to these design objectives is said to be a multiobjective optimization problem because of the conflicting relations between the design objectives.

5. Optimization procedure and results

In our implementation, we used 100 particles, the inertia weight was chosen as 0.25, and the algorithm was run for 400 iterations. Objective functions were established as follows.

$$OF_1 = \min \left(\frac{1}{f_2 - f_1} \right) \quad (18)$$

$$OF_2 = \min \left(\frac{\sum_{f=f_1}^{f_2} |S_{11}(f) \times S_{12}(f) \times S_{22}(f)|}{\sum_{f=f_1}^{f_2} |S_{21}(f)|^2} \right) \quad (19)$$

The first objective function represents the maximizing operation bandwidth; here, f_1 is set to 1 GHz and f_2 is equal to the maximum frequency value where $|S_{21}| > 1$. The other objective function aims to minimize losses and maximize the transducer power gain.

The modified PSO algorithm was implemented to the objective functions and a fast and elitist method, the NSGA-II [7-8] algorithm, was implemented to the FET modeling problem. Figure 4 shows the results of the modified PSO algorithm and the NSGA-II algorithm. At the end of 400 iterations, 77 particles converged to the resulting Pareto front. As shown, the modified PSO algorithm has an efficient Pareto front performance. Furthermore, the algorithm is capable of obtaining an expanded Pareto front (Pareto A and Pareto C points).

In order to demonstrate the conflicting relation between the design objectives, 3 sample optimal solutions were chosen. FET model element values ensuring these optimal solutions are given in the Table. Scattering parameters and transducer power gain variations of the FET models chosen from the Pareto optimal solutions are given in Figures 5 and 6, respectively. It can be seen from Figure 4 that the FET model corresponding to the Pareto A solution ensures the maximum operation bandwidth and highest transducer power gains among the chosen solutions. However, because of the conflicting behavior, the highest loss values occur for this FET model. The Pareto C point offers a compromise, with lower gain, lower losses, and a narrow bandwidth. The FET model resulting in the Pareto B solution has average levels for all of the design objectives, as shown in Figures 5 and 6.

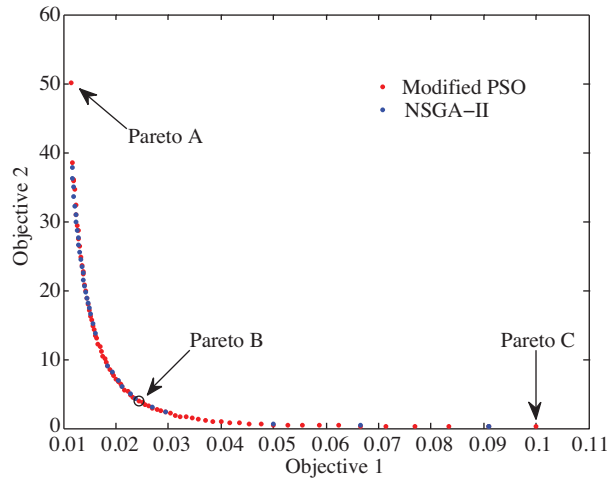


Figure 4. Comparison of modified PSO and NSGA-II algorithms.

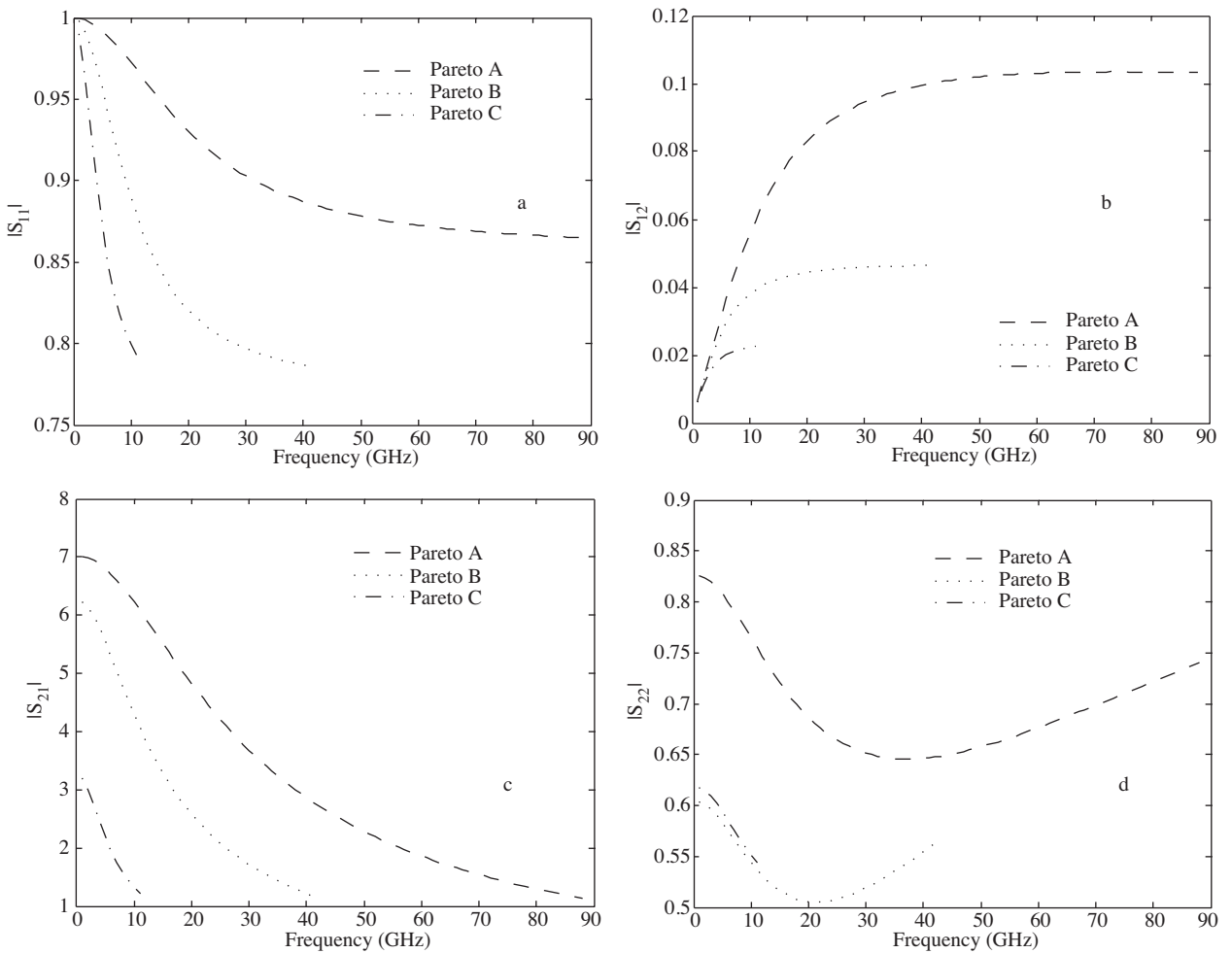


Figure 5. S-parameters of FET models chosen from Pareto optimal solutions.

Table. FET model element values.

FET model elements	Pareto A	Pareto B	Pareto C	Solution space	
g_m (S)	0.0782	0.0792	0.0417	0.04	0.08
C_{gs} (pF)	0.1040	0.2515	0.5906	0.1	0.6
R_i (Ω)	3.0604	5.5806	5.9458	2	6
C_{ds} (pF)	0.0231	0.0538	0.0782	0.02	0.08
R_{ds} (Ω)	517.83	200.14	206.02	200	600
C_{gd} (pF)	0.0103	0.0100	0.0101	0.01	0.02
r_g (Ω)	0.5647	0.7074	0.5290	0.1	1
r_d (Ω)	0.4330	0.8301	0.2786	0.1	1
r_s (Ω)	0.2044	0.1189	0.6168	0.1	1

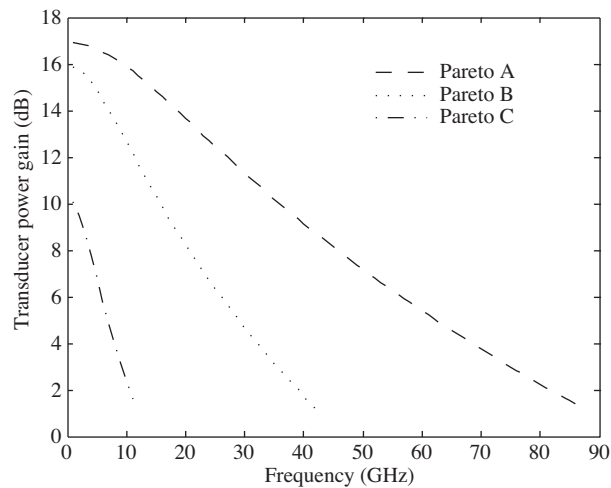


Figure 6. Transducer power gain variation of the FET models chosen from Pareto optimal solutions.

6. Conclusion

In this work, a modified PSO algorithm was introduced and the performance of the algorithm was investigated by implementation to the 9-dimensional multiobjective FET device modeling problem. The results show that the proposed algorithm can handle multiobjective optimization problems. As future work, implementation of the algorithm to several benchmark test functions and comparison with other multiobjective PSO algorithms is planned.

References

- [1] P.G. Alotto, B. Brandstatter, E. Cela, G. Furntratt, C. Magele, G. Molinari, M. Nervi, K. Preis, M. Repetto, K.R. Richter, "Stochastic algorithms in electromagnetic optimization", IEEE Transactions on Magnetics, Vol. 34, pp. 3674-3684, 1998
- [2] J. Kennedy, R.C. Eberhart, "Particle swarm optimization", Proceedings of IEEE Conference on Neural Networks, Vol. 4, pp. 1942-1948, 1995.

- [3] S. Mostaghim, J. Teich, "Strategies for finding good local guides in multi-objective particle swarm optimization (MOPSO)", IEEE 2003 Swarm Intelligence Symposium, pp. 26-33, 2003.
- [4] X. Hu, R. Eberhart, "Multiobjective optimization using dynamic neighborhood particle swarm optimization", IEEE Proceedings of World Congress on Computational Intelligence, pp. 1677-1681, 2002.
- [5] T. Günel, "A continuous hybrid approach to the FET modelling for the maximum transducer power gain", Microwave and Optical Technology Letters, Vol. 35, pp. 348-351, 2002.
- [6] C. Paoloni, "A simplified procedure to calculate the power gain definitions of FET's", IEEE Transactions on Microwave Theory and Technique, Vol. 48, pp. 470-474, 2000.
- [7] K. Deb, A. Pratap, S. Agrawal, T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II", IEEE Transactions on Evolutionary Computation, Vol. 6, pp.182-197, 2002.
- [8] K. Deb, Multi-Objective Optimization Using Evolutionary Algorithms, Chichester, UK, John Wiley & Sons, 2004.