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Artificial bee colony algorithm for small signal model parameter extraction of MESFET

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ABSTRACT

This paper presents an application of swarm intelligence technique namely artificial bee colony (ABC) to extract the small signal equivalent circuit model parameters of GaAs metal extended semiconductor field effect transistor (MESFET) device and compares its performance with particle swarm optimization (PSO) algorithm. Parameter extraction in MESFET process involves minimizing the error, which is measured as the difference between modeled and measured *S* parameter over a broad frequency range. This error surface is viewed as a multi-modal error surface and robust optimization algorithms are required to solve this kind of problem. This paper proposes an ABC algorithm that simulates the foraging behavior of honey bee swarm for model parameter extraction. The performance comparison of both the algorithms (ABC and PSO) are compared with respect to computational time and the quality of solutions (QoS). The simulation results illustrate that these techniques extract accurately the 16—element small signal model parameters of MESFET. The efficiency of this approach is demonstrated by a good fit between the measured and modeled *S*-parameter data over a frequency range of 0.5–25 GHz.

1. Introduction

Small signal model parameter extraction of MESFET involves extraction of extrinsic and intrinsic model element values (Lin and Kompa, 1994) by minimizing the difference between modeled and measured *S*-parameter over a broad range of frequencies. In the recent past, different techniques (Yaser, 2000; Van Niekerk et al., 2000) have been reported in the literature for extracting the model parameters of MESFET. These techniques are normally based on either analytical or numerical optimization techniques. Although analytical methods provide faster solution, the quality of solution (QoS) is normally poor. To improve QoS, methods based on numerical optimization are being increasingly used for parameter extraction. Numerical optimization techniques are either gradient-based or gradient-free. Possibility of having a multimodal error surface is an important extraction challenge in parameter extraction problem. In order to find a quality solution, an extraction algorithm that can achieve the global minima in multimodal error surface is required. However, the conventional gradient based approach that are used in past, can easily be trapped in local minima. Many researchers have proposed global optimization techniques like genetic algorithm (GA) (Gao, 2001; Watts et al., 1999; Menozzi et al., 1996) to extract the small signal model parameters of the MESFET.

Since a typical small signal parameter extraction problem has a multimodal error surface and it involves a large set (i.e. 16 number of elements), conventional gradient based techniques fails to provide QoS. In some cases, GA cannot guarantee global solution due to the diversity of population (Leung et al., 1997). Swarm intelligence has become a research interest to different domain of researchers in recent years. These algorithms simulate the food foraging behavior of a flock of birds or swarm of bees. Particle swarm optimization and its variants have been introduced for solving numerical optimization problems and successfully applied to solve many real world problems (Eberhart and Kenedy, 1995b; Sabat et al., 2009, 2010). PSO algorithm is a population based stochastic optimization technique and suitable for optimizing nonlinear multimodal error function. Motivated by the foraging behavior of honeybees, researchers have (Riley et al., 2005; Karaboga, 2009) initially proposed artificial bee colony (ABC) algorithm for solving various optimization problems. ABC is a relatively new population-based meta-heuristic approach and is further improved by Karaboga and Basturk (2008). This algorithm is easy to implement and found to be robust. Some recent results illustrate that artificial bee colony (ABC) algorithms outperforms basic PSO algorithm in terms of QoS (Karaboga and Basturk, 2008). The PSO and ABC algorithms are population based

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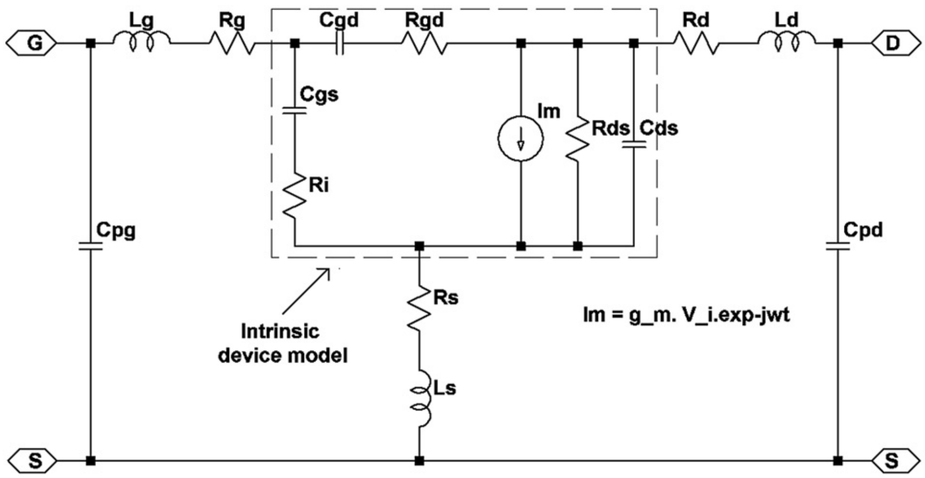

Fig. 1. Schematic diagram of MESFET small signal model.

evolutional meta-heuristic optimization algorithms that avoids trapping of solution in local minima. The objective of this paper is to use ABC algorithm for extracting the small signal parameters and to compare relative performances in terms of computational cost and QoS with that of basic PSO algorithm.

Fig. 1 shows a 16 element small signal equivalent circuit adopted for parameter extraction. It has eight extrinsic and eight intrinsic parameters. Extrinsic parameters are bias independent whereas intrinsic parameters are bias dependent. The methodology for extracting these parameters essentially involves minimization of the difference between measured and modeled S-parameter values under dc bias conditions.

Rest of the paper is organized as follows: Section 2 presents a brief description of the model parameter extraction strategies and formulation of the problem. Brief descriptions of PSO and ABC algorithms are provided in Sections 3 and 4, respectively. Section 5 presents the simulation results. Conclusions are drawn in Section 6.

2. Parameter extraction problem in MESFET

The main objective of small signal model parameter extraction problem is to minimize the difference between measured and simulated S-parameter at different bias points.

The fitness function is defined as

$$F(x) = \sum_{i=1}^{N} [\alpha_i(x)]^2 \quad (1)$$

where

$$\alpha_i(x) = \sum_{t=1}^{M} \sum_{j=1}^{2} \sum_{k=1}^{2} \frac{1}{\sigma_{jk}(t, w_i)} |S_{jk}(t, w_i) - \hat{S}_{jk}(t, w_i)|^2 \quad (2)$$

and

$$\sigma_{jk}(t, w_i) = |\hat{S}_{jk}(t, w_i)|_{\max} \quad (3)$$

Eq. (1) is the sum of errors at all the frequencies and Eq. (2) is the modeling error at all the bias points for all the four S-parameters at i th frequency w_i. The measured and modeled S-parameters of the MESFET at i th frequency and t th bias point are $S_{jk}(t,w_i)$ and $\hat{S}_{jk}(t, w_i)$, respectively. M is the number of bias points and N is the number of frequency points used in measurement. j and k are the indices of the four S-parameters. $\sigma_{jk}(t)$ is a normalization constant at t th bias point. x is the vector that has all the bias independent and bias dependent parameters need to be extracted.

Table 1
Model element/subfunction used for 16 element MESFET model.

No.	Model element	Bias dependent	subfunction to be minimized
1	C_{gs}, R_i	Yes	S_{11} at specific bias point
2	C_{gd}	Yes	S_{12} at specific bias point
3	g_m, τ	Yes	S_{21} at specific bias point
4	C_{ds}, R_{ds}	Yes	S_{22} at specific bias point
5	C_{pg}, R_g, L_g	No	S_{11} at all the bias point
6	C_{pd}, R_d, L_d	No	S_{22} at all the bias point
7	R_s, L_s	No	S_{12} at all the bias point

This fitness function (see Eq. (1)) can be divided into two parts, one for extracting bias independent model parameters and the other for extracting bias dependent model parameters. Bias dependent model parameters are associated with a modeling error due to the associated S-parameters at specified bias point as in Table 1. The fitness sub-function is given by

$$f_{ext}(w) = \sum_{i=1}^{N} |S_{jk}(t, w_i) - \hat{S}_{jk}(t, w_i)|^2 \quad (4)$$

similarly for obtaining bias independent model parameters, the fitness sub-function is defined as

$$f_{int}(x) = \sum_{i=1}^{N} \left(\sum_{t=1}^{M} \frac{1}{\sigma_{jk}(t, w_i)} |S_{jk}(t, w_i) - \hat{S}_{jk}(t, w_i)| \right)^2 \quad (5)$$

Table 1 presents different model parameters and their dependence with different S-parameters. For analysis purposes, the small signal equivalent circuit elements of MESFET, see Fig. 1, are grouped into two set of parameters: extrinsic and intrinsic. The extrinsic set consist of bias independent elements associated with the leads and contacts to the device such as C_{pg}, C_{pd}, L_g, L_d, L_s, R_g, R_d, and R_s. The intrinsic set consists of bias dependent parameters such as C_{gs}, R_i, C_{gd}, R_{gd}, C_{ds}, R_{ds} and g_m, τ.

The technique employed for parameter extraction is implemented in two stages. In the first stage, the extrinsic parameters are extracted from measured S-parameters under cold bias conditions i.e., V_{ds}=0 V and $V_{gs} < V_p$, where V_p is pinch-off voltage. Intrinsic parameters are extracted from measured S-parameters under hot bias condition ($V_{ds} > 0$ V and $V_{gs} < 0$ V) using suitable de-embedding technique in the second stage. Parameters to be extracted are initialized, each within carefully chosen and well defined range at the beginning of the extraction algorithm.

Different S parameter values are optimized for obtaining the different set of model elements of the equivalent circuit (Lin and