Parameter Extraction Method Using Hybrid Artificial Bee Colony Algorithm for an OFET Compact Model

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***Abstract*— Research on organic field effect transistors (OFETs) have been dramatically increased in the last decade, considering their lightweight and flexible structure as well as their practical and low-cost production. Building compact models and parameter extraction methods have also a critical importance in extensively using OFETs in electronic systems. In this paper, we propose a hybrid artificial bee colony algorithm as a parameter extraction tool and we compare it with purely mathematical and genetic algorithm-based parameter extraction methods. We apply these methods to a well-known OFET compact model for two different transistors, both having pentacene as organic semiconductor. First transistor (T1) is available in literature and the other one (T2) is fabricated in our laboratory. The proposed approach shows a good agreement with the experimental data of T1 with normalized RMS error (NRMSE) of 0.26%. However, it is 1.83% for T2 due to lack of measurements. If the shape of the data was same, the parameter extraction approaches would be expected to perform more successfully for both OFETs as well. Results are tabulated and performances of the methods are compared in the paper.**

Keywords—Compact models, Organic field effect transistor (OFET), parameter extraction, artificial bee colony algorithm, genetic algorithm

I. Introduction

Organic field effect transistors (OFETs) attract interest, especially in experimental and fabrication levels. High quality organic materials, better contacts and more stable devices are becoming available. However, there are still gaps about the compact, generic models to simulate OFET circuits and systems. Since the charge transport mechanisms of the organic semiconductors are not understood completely, purely physical models lack accuracy. In this regard, parameter extraction techniques step forward through the algorithms to process the experimental data.

There are several types of compact models but we can simply categorize these models in two groups as physical and empirical compact models. Physical compact models can predict the behaviour of transistors better and can be adapted by simply changing parameters. In these models, all the parameters have a physical explanation. These models are also hard and tedious. In empirical models, it is also possible to fit the experimental measurements but parameters have no physical meaning in this case. Hence, empirical models are not predictive. Increasing accuracy of the model is accompanied by the complexity and complex models contain considerable number of parameters. Conventional methods used for parameter extraction are mathematical-based direct parameter extraction tools. Unified model and parameter extraction method (UMEM) is one of them and it needs human experience in order to be carried out properly [1]. In OFETs, UMEM method is practiced in recent years [2, 3]. In order to model the behaviour of the OFET and extract parameters of it for the experimental data, analytical expressions are used for UMEM method. There are some parameters correlated with each other, hence it is a complex task. In this situation, introducing global optimization methods would be a remarkable solution to extract parameters [1].

Evolutionary algorithms like SaPOSM [4], fast diffusion [5], and genetic algorithms [6] are researched to be able to determine the set of model parameters that can fit the experimental data. Genetic algorithm (GA) is commonly used to solve compelling problems. Its robustness in transistor devices are presented in literature [7, 8]. GA is simple, easy for coding and applicable in order to extract parameters. Nevertheless, GA cannot provide global solution due to the diversity of population in some instances [9]. Swarm intelligence is also a research interest for solving miscellaneous optimization problems. Artificial bee colony (ABC) algorithm is proposed as a metaheuristic search algorithm for this purpose and is improved by Karaboga and Basturk [10]. Implementation of ABC algorithm is easy and it is really robust. Furthermore, it prevents trapping in local minima for the solution [11]. That's why we have also applied a hybrid artificial bee colony algorithm (h-ABC) beside GA for parameter extraction of OFET models in this paper.

In addition to GA based approaches [8] for OFETs in literature, we propose a method based on h-ABC algorithm. These extraction methods are applied to Estrada's [2] compact model for two different transistors. The first transistor data is available in literature and its structure is bottom-gate, top-contact. The other transistor is fabricated in our laboratory and its structure is bottom-gate, bottom-contact. Both transistors have pentacene active layer. As in this case, testing parameter extracting techniques for different structures will also give us information about the applicability of the model to other type of device structures and moreover, it is important to achieve more comprehensive models. In the later sections, we will show the results and compare their performances.

This paper is organized as follows: Section 2 presents the OFET compact model. Section 3 provides the brief description of the proposed h-ABC algorithm. Finally sections 4 and 5 give the simulation results and conclusion respectively.

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II. BACKGROUND: OFET COMPACT MODEL

The parameter extraction techniques have been applied to the organic TFT model [2]. The results are compared with the parameters extracted analytically. Cerdeira et al. [12] proposed an analytical method to calculate parameters of the model. In this model, the mobility depends on gate voltage as shown in (1):

$$\mu_{FET} = \mu_0 \left(\frac{V_{GS} - V_T}{V_{AA}} \right)^{\gamma_a} = \mu_{FET0} \left(V_{GS} - V_T \right)^{\gamma_a} \qquad (1)$$

where V_T is the threshold voltage, μ_0 is the band mobility for the OFET, γ_a and V_{AA} are fitting parameters to adjust μ_{FET}.

Equation 2 gives the drain current in the linear and saturation regions for the above threshold regime as:

$$I_{DS} = \frac{\left(K / V_{AA}^{\gamma} \right) \left(V_{GS} - V_T \right)^{1+\gamma}}{1 + R \left(K / V_{AA}^{\gamma} \right) \left(V_{GS} - V_T \right)^{1+\gamma}} \times \frac{V_{DS} \left(1 + \lambda V_{DS} \right)}{\left(1 + \left(\frac{V_{DS}}{V_{DSAT}} \right)^m \right)^{\frac{1}{m}}} \qquad (2)$$

where $K=(W/L)C_i\mu_0$, W and L are channel dimensions, C_i is insulator capacitance, R is the sum of source and drain resistances, m is to adjust how sharp the knee region is and λ is channel length modulation parameter. In addition, α_s parameter is used to calculate saturation voltage as $V_{DSAT} = \alpha_s(V_{GS}-V_T)$. Parameter α_s is usually taken less than one.

In linear region, drain current equation with the effect of series resistance is written as following:

$$I_{DSlin} = \frac{K / V_{AA}^{\gamma}}{1 + R \left(K / V_{AA}^{\gamma} \right) \left(V_{GS} - V_T \right)^{1+\gamma}} \left(V_{GS} - V_T \right)^{1+\gamma} V_{DS} \qquad (3)$$

III. THE PROPOSED PARAMETER EXTRACTION METHOD

Hybrid Artificial Bee Colony Algorithm:

Artificial bee colony algorithm introduced by Karaboga [13] is a swarm intelligent algorithm. In this case, a hybrid variant of ABC algorithm is applied as a parameter extraction technique. Introducing crossover to canonical ABC algorithm makes it hybrid, since crossover is known as a genetic algorithm operator. Hybrid ABC algorithm steps are shown in Fig. 1.

First of all, food sources are generated randomly by (5). Food sources correspond to parameter sets for OFET model. Thereafter fitness function is evaluated and the nectar amount is determined. Normalized RMS error given in (4) is used for the fitness function.

$$NRMSE = \frac{1}{I_{\max} - I_{\min}} \left(\sqrt{\frac{\sum_{i=1}^{N} \left(I_i - \hat{I}_i \right)^2}{N}} \right) \qquad (4)$$

where I_i and $\hat{I}_i$ is the measured and extracted values of I_{DS} of OFETs. N is the total number of calculated currents.

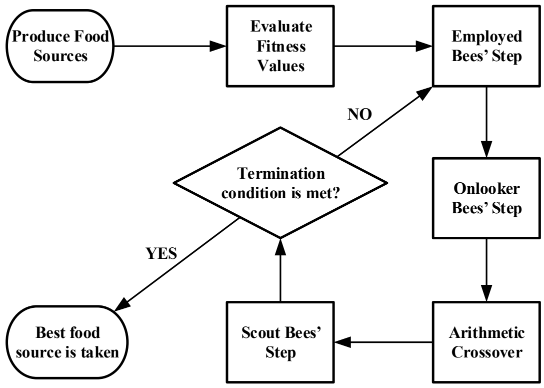

Fig. 1. The flowchart of h-ABC algorithm

Employed bees are sent to the food source and they search for a neighbouring food source. The new food sources are produced according to (6) and their fitness values are evaluated.

$$x_{i.j} = x_j^{\min} + rand(0,1)\left(x_{j\max} - x_{j\min} \right) \qquad (5)$$

where i varies from 1 to number of food sources and j varies from 1 to dimension of the problem. x_{jmin} and x_{jmax} are minimum and maximum limits of the jth parameter.

By applying greedy selection on the new and firstly produced food sources, the better foods are stored in the memory. The trials counter is defined to find out whether the food source did really improved. If the food source is better than the previous one the counter content is reset to zero, otherwise the counter is incremented by one until reaching predefined "limit" constant.

In the onlooker bees' step, the employed bees deliver their information to the onlookers and the onlookers goes to food source to utilize with regard to its nectar amount. The higher nectar amount is, the higher probability to be selected will be. The new one is produced in the neighbourhood of selected food source by (6) and their nectar amount is determined.

$$v_{i.j} = x_{i.j} + \phi\left(x_{i.j} - x_{k.j} \right) \qquad (6)$$

where k is a random dimension which locates a food source selected randomly different from i, j. ϕ is a random number in the range of [-1, 1]. The newly produced food source v is evaluated by changing dimensions of x. At this point, the new and old food sources are compared and a selection is made between them by greedy selection method.

In addition to original ABC algorithm, a crossover operator is added between onlooker bees and scout bees' steps. A number of food vectors are selected as parents with respect to their fitness for the crossover operator. The higher the fitness value is, the larger the probability to be selected will be. Parents are being selected by use of tournament selection. Arithmetic crossover produces linear combination of each parents with (7).

$$P_{new} = \alpha P_{ma} + (1-\alpha) P_{pa} \qquad (7)$$

where P_{ma} and P_{pa} are the parents, P_{new} is the offspring and α is a random number (0,1).

Hence the new offspring will be the good ones. The new offspring are compared with the food sources selected from food matrix according to crossover rate (CR). CR determines how much of the food sources will be selected. Greedy selection is applied here and the best ones are kept in the food matrix.

The final step is the scout bees' step. If there is no improvement until the control parameter, limit, is reached, then that food source is abandoned. The employed bee for that food source becomes a scout bee and the new food source is generated randomly in its boundaries by (5). The counter for the new food source is also cleared as well.

The steps of employed bees, onlooker bees, crossover and scout bees will be repeated until the termination conditions are met.

IV. RESULTS

Genetic and h-ABC algorithms are applied to extract model parameters for I-V measurements of T1 data from [14] and T2 pentacene data fabricated in our laboratory. Some physical parameters of the transistors are given in Table 1. GA is applied for the purpose of comparison. In our paper we do not give theoretical details of the GA and further reading can be done from [15]. In brief, we generate a population which consists of chromosomes randomly and evaluate fitness function. Each gene of the chromosomes corresponds to a model parameter. We defined the size of chromosomes and population as 7 and 100, respectively. Selection of parents for crossover is conducted by roulette wheel selection method and the offspring are produced by arithmetic crossover (7). Crossover and mutation rate is taken as 0.6 and 0.15, respectively. In h-ABC algorithm the population size is 100 and the number of employed and onlooker bees are 50. In crossover phase, parents are being selected with tournament selection method and (7) is applied as the crossover operator.

T1 has bottom-gate, top-contact structure with 100µm channel width and 10µm channel length. Its organic semiconductor is vacuum-deposited pentacene with 30nm thickness. The other details can be found in [14]. T2 has a bottom-gate, bottom-contact structure and thermally evaporated pentacene active layer is used on commercially available test chips (Ossila Ltd., Sheffield, UK) with channel width of 1mm and channel length of 20µm.

Equation (2) consists of all the parameters needed and is considered for genetic and h-ABC algorithms. For analytical extraction method, equation (1) is also considered and the steps given in [12] are followed. Experimental and calculated tranfer characteristic curves are shown in Fig. 2, and Fig. 3 as well as the output characteristic curves are shown in Fig. 4, and Fig. 5.

Transfer characteristics of T1 and T2 are calculated with V_{DS} = –0.1V and V_{DS} = –8V, respectively. The extracted parameters by analytical, GA and h-ABC algorithm methods are given in Table 2 for both T1 and T2. The parameter values are calculated by taking average of them after ten times running. The model with parameters extracted by GA and h-ABC fit very well with experimental data of T1 as shown in Fig.2 and Fig.4. However, the curves produced by analytical extraction method deviate a little bit from the experimental curves and I_{DS} level is lower than the others. Both algorithms work excellent with T1 data. Their performances are similar but h-ABC algorithm steps forward with less error of 0.26%.

Table 1. OFETs' constant parameters for simulations

Transistor	***W (µm)***	***L (µm)***	***C_i (F/cm2)***	***μ_0 (cm2/V.s)***
T1	100	10	$0.7*10^{-6}$	0.4
T2	1000	20	$1.09*10^{-8}$	0.25

Parameter extraction processes could also make the model produce similar characteristic curves to those plotted from experimental data for T2 as shown in Fig.3 and Fig.5. GA and h-ABC algorithms extract threshold voltage less and simulated model gives higher current than the experimental data for lower V_{GS}. Afterwards, it fits to the experimental data for larger V_{GS}. The proposed algorithm fits better for output curves of T2 as shown in Fig.5. Output curves have a small shift in lower V_{DS} range for all algorithms due to lack of data. In both cases, h-ABC algorithm gives the least error as shown in Table 2 and it is as fast as GA. In this case, runtime analysis is not crucial, considering the amount of data and less computational complexity of the model. Analytical method is tedious and did not perform better than the others, but it can be used to generate better initial population for other algorithms.

V. CONCLUSION

Parameter extraction approaches based on GA and h-ABC are implemented in this work for two OFETs (T1&T2) both having pentacene active layer. For T1, h-ABC and GA based approaches fit very well and results are acceptable. For the fabricated T2, parameters extracted by the proposed approach give the closest characteristic curves to those achieved experimentally. However, simulated model of T2 has less accuracy than the one of T1. We think that it arises from the lack of data for small V_{DS} in consequence of our data acquisition method. Considering the T1 case, we will upgrade our systematic data acquisition strategy to model all regions extensively for future works. The proposed algorithm is easy to implement and its performance is satisfactory. It can be applied to other OFET compact models as well. In the literature, there are also different mutation and crossover methods to improve the algorithms. We will apply them in future works to have more accurate and robust parameter extractor. Our primary target will be building robust and accurate compact models for different device structures and organic materials.

Table 2. Extracted OFET Model Parameters

#	**Method**	***V_T (V)***	**γ**	***V_{AA} (V)***	***R (Ω)***	**α_s**	***m***	***λ (1/V)***	**NRMSE**
T1	h-ABC	-1.02	0.76	1.58	87k	0.57	2.69	0.0069	0.0026 ± 28%
	GA	-1.10	0.51	1.66	65k	0.60	2.80	0.0037	0.0052 ± 21%
	Analytical Method[12]	-1.05	0.37	3.94	11k	0.53	2.68	0.02	0.0602
T2	h-ABC	-5.47	0.90	1983	59k	1.06	2.13	-0.0090	0.0183 ± 2%
	GA	-5.17	0.96	1498	150k	1.05	2.06	-0.0084	0.0190 ± 8%
	Analytical Method[12]	-6.90	1.08	891	47k	1.12	2.09	-0.0071	0.0225

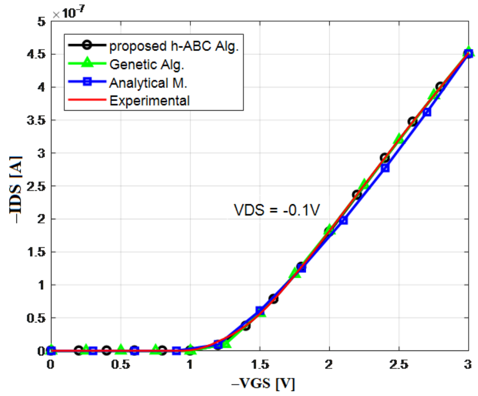

Fig. 2. Transfer Characteristic Curves for T1

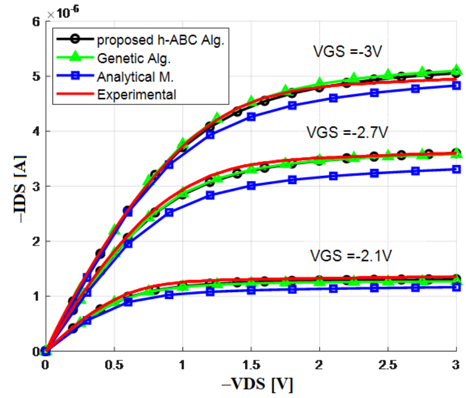

Fig. 4. Output Characteristic Curves for T1

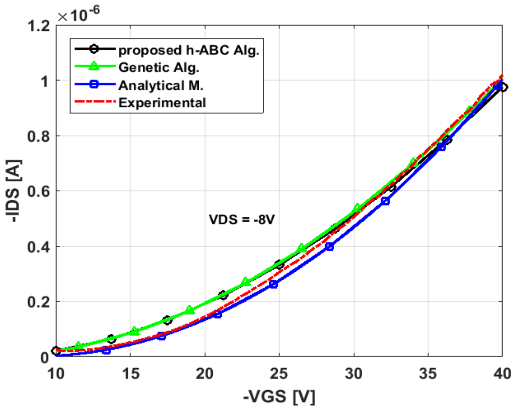

Fig. 3. Transfer Characteristic Curves for T2

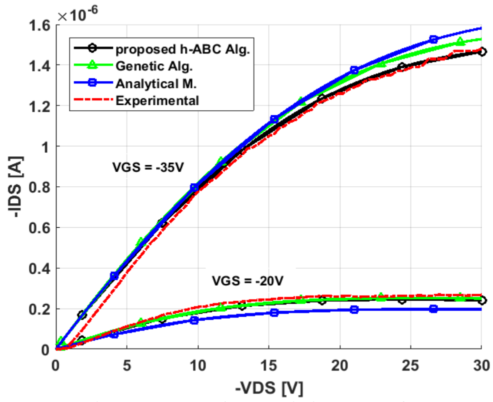

Fig. 5. Output Characteristic Curves for T2

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