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Modeling and Parameter Extraction of OFET Compact Models Using Metaheuristics-Based Approach

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ABSTRACT Research on the fabrication of organic field effect transistors (OFETs) has been dramatically increased in the last decade, considering their lightweight and flexible structure as well as their practical and low-cost production. In the next step of fabrication, building compact models and developing parameter extraction methods have critical importance in designing electronic circuits using fabricated OFETs. In this paper, we propose a parameter extraction approach which benefits from the power of metaheuristics. Although direct extraction tools offer analytical solutions in successive steps to extract model parameters, metaheuristics-based global optimization methods can find all parameters at once by exploring a wide range of parameters. Direct extraction tools are cumbersome and need human expertise. On the other hand, global optimization methods are very flexible, adaptive and can be automated as parameter extraction tools of any compact model. In this study, we introduce three different global optimization algorithms, namely, a genetic algorithm (GA), a hybrid artificial bee colony (h-ABC) algorithm, and bacterial foraging optimization (BFO) algorithm, for the parameter extraction. To the best of our knowledge, h-ABC and BFO algorithms have been used for the first time in extracting parameters of OFET compact models. We use two OFET compact models developed by Estrada *et al*. and Marinov *et al*. for two different datasets of OFET transistors, both having pentacene as organic semiconductor. While one of the dataset of transistor (T1) is available in literature, the dataset of the other transistor fabricated in our laboratory (T2) is generated as a new dataset. In order to tune control parameters of the developed algorithms, Taguchi's orthogonal experimental design (OED) method is used. Experimental results show that the proposed metaheuristics-based approach can extract model parameters successfully and can perform better than direct extraction methods. The studied OFET compact models fit to the experimental data with these parameters and predict similar output characteristic curves. The algorithms show a good agreement with the experimental data of T1 and T2, having normalized root-mean-square error values under 3.70%, and 8.74% for the models of Estrada *et al.* and Marinov *et al*., respectively. It is shown that h-ABC and BFO algorithms perform better than GA on average. It is also observed that the compact model by Estrada *et al.* performs better for both T1 and T2 compared to the model of Marinov *et al*.

INDEX TERMS Compact models, organic field effect transistor (ofet), parameter extraction, artificial bee colony algorithm, bacterial foraging algorithm, genetic algorithm, Taguchi method.

I. INTRODUCTION

Organic field effect transistors (OFETs) attract interest, especially in fabrication level. High quality organic materials, better contacts and more stable devices are becoming available [1]–[5]. OFETs are well studied in fabrication level, however compact models are not good enough to simulate OFET circuits and systems. Since the charge transport mechanism of the organic semiconductors are not understood completely, physical modelling is challenging [6]. Purely physical models lack accuracy because of variations in device structure, the choice of material among many available organic

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semiconductors and varying fabrication methods. We also observed this fact for the fabrications in our lab. On the other hand, purely physical models might include more complicated equations; they are slow and we may encounter convergence problems. Hence, they are not good enough for a CAD model. Fortunately, compact modeling can work out the mentioned shortcomings. In the literature there are some compact modeling works for organic transistors [7]–[13]. In this paper, another two well-known OFET compact models developed by Estrada *et al*. [14], and Marinov *et al*. [15] are studied. These compact models have various parameters and they need to be extracted accurately to be able to simulate electrical characteristics of OFETs. At this point, parameter extraction methods play a critical role. Conventional methods used for parameter extraction are mathematical based direct extraction tools. Unified model and parameter extraction method (UMEM) is a good example for them and has been practiced for OFETs in recent years [14], [16], [17]; however, it needs human experience to be carried out properly [18]. On the other hand, Yaglioglu *et al*. [19] reports a methodology to extract model parameters of Silvaco's Universal Organic TFT compact model using transfer line method (TLM). Jung *et al*. [20] presents a drain current model and provide a parameter extraction method using TLM and ratio method. These direct extraction tools are constructed on analytical expressions with a step by step procedure to extract parameters. However, some parameters are difficult to be extracted simultaneously since they are correlated with each other. As a result, it is quite hard to develop a systematic methodology. For this reason, we use global optimization methods. They are advantageous because of their global search abilities which explore wide range of parameters. All of the parameters can be found at once and accurate results can be obtained with fast optimization. Global optimization methods are also very flexible and easily adaptable to different models; they can be automatized as parameter extractor tools of any compact model.

Among different global optimization methods, evolutionary algorithms like SaPOSM [21], fast diffusion [22], and genetic algorithm (GA) [23] are researched. GA is commonly used to solve compelling problems. Its robustness in transistor devices are presented in the literature [24], [25]. Nevertheless, GA cannot provide global solution due to the diversity of population in some instances [26]. Recently, Romero *et al*. proposed evolutionary parameter extraction procedure for OTFTs considering contact effects [27] and Fatima *et al*. extracted parameters of various OFET compact models using global extraction technique based on particle swarm optimization algorithm [28]. Swarm intelligence is another research interest for solving miscellaneous optimization problems. In this regard, we have investigated artificial bee colony (ABC) and bacterial foraging optimization (BFO) algorithms as swarm algorithms, motivated by their local and global search abilities. In the literature, an ABC algorithm is proposed as a metaheuristic search algorithm and it is improved by Karaboga and Basturk [29]. Implementation of the ABC algorithm is easy, and it is quite robust. Furthermore, it prevents trapping in local minima for the solution [30]. We use an ABC algorithm hybridized by crossover operator of GA. The other optimization algorithm proposed by Passino [31] is BFO algorithm. The foraging strategy of Escherichia coli, commonly known as E. coli, bacteria is mimicked in this algorithm. It is stated that the BFO algorithm can converge to the global minima faster than GA [32].

In this article we present a systematic parameter extraction approach which benefits from the power of metaheuristics for OFET compact models. Its performance is compared with the direct extraction method proposed by [16] for the model equation of Estrada *et al*. and then it is validated for another OFET compact model of Marinov *et al*. and the method given in [33]. To the best of our knowledge, BFO and h-ABC algorithms have not yet been applied as global parameter extraction techniques for OFET compact models contrary to GA. Therefore, we decide to show the performance of the proposed metaheuristics-based extraction method using three different metaheuristics. In addition, there is no detailed work about how to select the control parameters of GA, BFO and h-ABC algorithms for parameter extraction of OFET compact models. Here, we optimize the control parameters of these algorithms by exploiting Taguchi's Orthogonal Experimental Design (OED) method. Control parameters need to be tuned according to a specific problem and they directly affect the convergence performances of the algorithms. It is time consuming tuning these control parameters. If the number of control parameters are n and each one of them can take k different values, then we need k^n experiments. In order to reduce experiments and converge near to an optimal solution, Taguchi's OED is a useful method. [34], [35].

For experiments, we use two different datasets of OFET transistors. The first transistor data is available in the 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 layers. As a result, we have four test cases for each of the three algorithms for comprehensive evaluations.

This paper is organized as follows: Section II presents the used OFET compact models. Section III provides the parameter extraction process and brief description of the used genetic, h-ABC, and BFO algorithms. Finally, Section IV and V give the simulation results and conclusions, respectively.

II. BACKGROUND: OFET COMPACT MODELS

From the literature, two well-known OFET compact models proposed by Estrada *et al*. and Marinov *et al*. are chosen.

Estrada *et al*. applied the unified model and parameter extraction method (UMEM) to organic thin film transistors. They say that the method can be used for devices with different geometries and fabrication conditions providing the same parameter extraction conditions [14]. In the model, power-law dependency is seen between mobility and gate overdrive voltage.

Marinov *et al.* [15] derived an analytical generic organic thin film transistor model. This compact model provides all operation regimes of OFET. In the background of OFET studies, researchers benefit from well-known important theories such as tail-distributed traps and variable range hopping. These theories give a common point to start modeling.

Following this brief explanation, model equations are given in sub-sections below.

A. MODEL BY ESTRADA ET AL.

In this model, the mobility depends on gate voltage as following equation:

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

where μ_{FET} is the field effect mobility; μ_0 is the band mobility for the OFET; μ_{FET0} is the mobility value for low perpendicular and longitudinal electric field; V_{GS} is the gate-source voltage; V_T is the threshold voltage; γ and V_{AA} are fitting parameters to adjust μ_{FET}.

The equation below gives the drain current in the linear and saturation regimes for the above threshold regime as:

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

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

B. MODEL BY MARINOV ET AL.

In this model, the authors [15] use an expression for the gate voltage dependent mobility that is $\mu \propto (V_G - V_T)^{\gamma}, \gamma > 0$. A familiar concept of charge drift is used to derive the charge drift model and it is given in TFT by

$$\frac{I_{Mar}}{W} = Q_{Mar}(x)\,\mu_{Mar}(x)\,\frac{dV}{dx} \quad (3)$$

where W is the channel width of the TFT. The density of hole charge at a given position of x $(0 \leq x \leq L)$ is expressed by

$$Q_{Mar}(x) = -C_i\left[(V_G - V_T) - V(x)\right] \quad (4)$$

here V_G is the gate electrode voltage; $V(0) = V_S$ and $V(L) = V_D$; V_S and V_D are source and drain electrode voltages, respectively.

Mobility equation is written from theories given in [36] and [37] as follows

$$\mu_{Mar}(x) = \frac{\mu_0}{V_{AA}^{\gamma}}\left\{-\left[(V_G - V_T) - V(x)\right]\right\}^{\gamma} \quad (5)$$

TABLE 1. To be extracted parameters for OFET compact models.

Model	P1	P2	P3	P4	P5	P6	P7	P8
Estrada	μ_0	V_T	γ	V_{AA}	R	α_s	m	λ
Marinov	μ_0	V_T	V_{SS}	V_{AA}	γ	λ		

Integrating (3),

$$\int_0^L \frac{I_{Mar}}{W} dx = \int_{V_s}^{V_D} \mu_{Mar}(x)\, Q_{Mar}(x)\, \frac{dV}{dx} \quad (6)$$

and substituting $Q_{Mar}(x)$ and $\mu_{Mar}(x)$, we get

$$I_{Mar} = \frac{W}{L}\frac{\mu_0}{V_{AA}^{\gamma}} C_i \times \frac{\left\{-\left[(V_G - V_T) - V_D\right]^{\gamma+2}\right\} - \left\{-\left[(V_G - V_T) - V_S\right]^{\gamma+2}\right\}}{\gamma + 2} \quad (7)$$

The subthreshold regime can be added by an asymptotically interpolation function. It is given that the effective gate overdrive voltage is as follows:

$$f(V_G, V) = V_{SS} ln\left\{1 + exp\left[-\frac{(V_G - V_T) - V}{V_{SS}}\right]\right\} \quad (8)$$

here, V_{SS} corresponds to the slope of the exponential current. As a result, the final compact TFT model is as follows

$$I_{Mar}^{com} = \frac{W}{L}\frac{\mu_0}{V_{AA}^{\gamma}} C_i \times \frac{\left[f(V_G, V_D)\right]^{\gamma+2} - \left[f(V_G, V_S)\right]^{\gamma+2}}{\gamma + 2} \times (1 + \lambda\,|V_D - V_S|) \quad (9)$$

It is stated that model characterizes the transfer curves' upward bending on a linear scale by gate voltage enhancement of mobility. On the other hand, the model can incorporate contact voltage drop V_C by taking $V_S = V_C$ in (7) and (9). Since V_C is a function of drain current, this effect is ignored in our work.

All the extracted parameters are tabulated in Table 1.

III. THE PROPOSED PARAMETER EXTRACTION METHOD USING METAHEURISTICS

In this paper, we follow a metaheuristics-based approach to extract parameters of the OFET compact models given in previous section. This approach is illustrated in Fig. 1. We select only three characteristic curves instead of feeding the whole data to the extractor. Two of them are transfer characteristic curves in linear and saturation regimes. The third one is an output characteristic curve that covers the transition from linear regime to saturation regime, and it is selected for the gate bias near the maximum gate voltage. While the first transfer curve covers linear regime as much as possible, the second transfer curve must cover the saturation regime as much as possible. For example, the maximum operating voltage is ±3V for T1 transistor and two transfer characteristic curves of $V_{DS} = -0.1$V and $V_{DS} = -1.5$V are taken as data to extract model parameters. Likewise, the operating voltage is

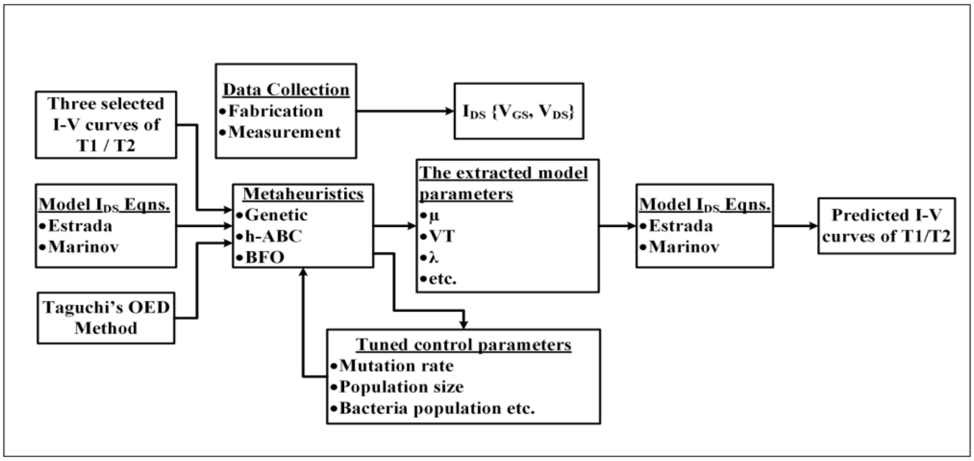

FIGURE 1. Illustration of the parameter extraction process.

±40V for T2 transistor and two transfer characteristic curves of $V_{DS} = -4$V and $V_{DS} = -40$V are taken. Instead of $V_{DS} = -4$V a lower voltage could be taken, however our measurement step size was set as 4V. Since data were very noisy for lower drain voltages. The third output curve is important for extracting parameters related to the transition from linear regime to saturation regime and channel length modulation.

When the data is ready, it is fed to the algorithms and all model parameters are extracted for two different OFETs. We firstly compare the proposed metaheuristics-based parameter extraction approach with the direct extraction method given in [16] for the model of Estrada *et al.* After showing its sufficient performance we validate it for another OFET compact model of Marinov *et al*. This validation is important to test its global applicability to other OFET compact models too. With this motivation we set up $2 \times 3 \times 2$ different experiments using 2 OFET models, 3 metaheuristics-based optimization algorithm and 2 different OFET devices. In each experiment control parameters of the algorithms are also optimized by conducting sub-experiments. Genetic, hybrid artificial bee colony and bacterial foraging optimization algorithms are applied to extract model parameters as metaheuristics. Using parameters extracted from the selected characteristic curves for each model, the other output characteristic curves are simulated in order to see whether the OFET compact models can predict them acceptably. In this way, the successful performance of the proposed metaheuristics-based parameter extraction procedure for OFET compact models is showed.

Taguchi's Orthogonal Experimental Design method is used to design experiments determining control parameters of each algorithm with a small number of experiments. Orthogonal array is selected according to the number of control parameters and their level from the orthogonal array selector given in [38]. Three levels are chosen as low, medium and high. From previous experiments in the literature [18], [29], [31], [39], [40] and from our previous experiences, we determine an empiric medium value for each control parameter and then we set low and high values decreasing and increasing medium value linearly by considering their relative ranges in the literature. For example, medium value of reproduction steps count (N_{re}) is set as 15, and then subtracting and adding by 10 low value is set as 5 and high value is set as 25.

TABLE 2. The designed experiments for L9 Orthogonal Array.

$L_9(3^4)$ Orthogonal Array				
Experiment #	Factor A	Factor B	Factor C	Factor D
1	A1	B1	C1	D1
2	A1	B2	C2	D2
3	A1	B3	C3	D3
4	A2	B1	C2	D3
5	A2	B2	C3	D1
6	A2	B3	C1	D2
7	A3	B1	C3	D2
8	A3	B2	C1	D3
9	A3	B3	C2	D1

In genetic and h-ABC algorithms experiments are run based on L9 orthogonal array for 4 independent control factors that each has 3 factor level as shown in Table 2. L9 (3^4) means that 9 experiments will be performed to study 4 factors having 3 level. There are fully 81 (3^4) experiments but, fortunately L9 orthogonal array reduces them to only 9 experiments.

In BFO algorithm there are 7 control parameters and experiments are run based on L18 (3^7) orthogonal array for 7 control factors with 3 factor level as shown in Table 3. Instead of performing 3^7 experiments, we can have reasonable results with only 18 experiments. Each row is an experiment which includes the combination of control parameters for the algorithms in predefined order.

A. HYBRID ARTIFICIAL BEE COLONY ALGORITHM

Artificial bee colony algorithm introduced by Karaboga [41] is a swarm intelligence algorithm. In this case, a hybrid variant of ABC algorithm is applied as a parameter extraction technique. Introducing crossover to canonical

TABLE 3. The designed experiments for L18 Orthogonal Array.

$L_{18}(3^7)$ Orthogonal Array							
Exp#	Factor A	Fc. B	Fc. C	Fc. D	Fc. E	Fc. F	Fc. G
1	A1	B1	C1	D1	E1	F1	G1
2	A1	B2	C2	D2	E2	F2	G2
3	A1	B3	C3	D3	E3	F3	G3
4	A2	B1	C1	D2	E2	F3	G3
5	A2	B2	C2	D3	E3	F1	G1
6	A2	B3	C3	D1	E1	F2	G2
7	A3	B1	C2	D1	E3	F2	G3
8	A3	B2	C3	D2	E1	F3	G1
9	A3	B3	C1	D3	E2	F1	G2
10	A1	B1	C3	D3	E2	F2	G1
11	A1	B2	C1	D1	E3	F3	G2
12	A1	B3	C2	D2	E1	F1	G3
13	A2	B1	C2	D3	E1	F3	G2
14	A2	B2	C3	D1	E2	F1	G3
15	A2	B3	C1	D2	E3	F2	G1
16	A3	B1	C3	D2	E3	F1	G2
17	A3	B2	C1	D3	E1	F2	G3
18	A3	B3	C2	D1	E2	F3	G1

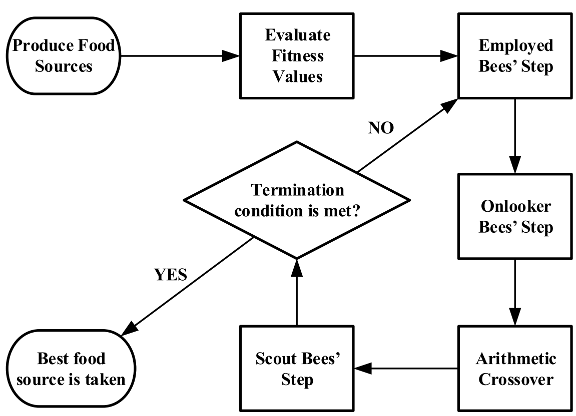

FIGURE 2. The flowchart of h-ABC algorithm.

ABC algorithm makes it hybrid, since crossover is known as a genetic algorithm operator. Hybrid ABC algorithm steps are shown in Fig. 2.

First of all, food sources are generated randomly by following equation:

$$x_{ij} = x_{jmin} + rand(0, 1)\left(x_{jmax} - x_{jmin}\right) \tag{10}$$

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 j^{th} parameter.

Food sources correspond to parameter sets for OFET model. Thereafter fitness function is evaluated, the nectar amount is determined. Normalized RMS error given below is used for the fitness function [27].

$$NRMSE = \left(\sqrt{\frac{\sum_{i=1}^{N}\left(I_i - \hat{I}_i\right)^2}{\sum_{i=1}^{N}\left(I_i - \bar{I}\right)^2}}\right) \tag{11}$$

where I_i and $\hat{I}_i$ is the measured data and the simulated outputs; $\bar{I}$ is the mean value of I_{DS} data of OFETs. N is the total number of current samples.

Employed bees are sent to the food source and they search for a neighboring food source. The new food sources are produced according to (12) and their fitness values are evaluated.

$$v_{ij} = x_{ij} + \varphi\left(x_{ij} - x_{kj}\right) \tag{12}$$

where k is a random dimension which locates a food selected randomly different from i, j; φ is a random number in the range of $[-1, 1]$.

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 improve. 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. "limit" control parameter plays an important role on the performance of h-ABC algorithm, because the search goes on intensively until maximum limit is reached and if the nutrient is poor then search space is changed. Clearly, it helps reducing the computational complexity [42].

In the onlooker bees' step, the employed bees deliver their information to the onlookers; and the onlookers go 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 neighborhood of selected food source by (12) and their nectar amount is determined. The newly produced food source v is evaluated by changing dimensions of x. At this point, a selection is made between the new and old food sources by greedy selection method.

In addition to the canonical 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 using of tournament selection method. Arithmetic crossover produces linear combination of each parents as follows:

$$P_{new} = \alpha P_{ma} + (1 - \alpha)P_{pa} \tag{13}$$

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 are expected to be the better 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 are selected. Greedy selection is applied here, and the best ones are kept in the food matrix. Introducing crossover operator into ABC algorithm provides faster convergence [43] and choosing CR control parameter will affect the performance of the algorithm. The final step is the scout bees' step. If there is no improvement until the control parameter named as "limit" is reached to the predefined value, 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

TABLE 4. The control parameters of h-ABC algorithm to set up.

	OFET Compact Models			
	Estrada *et al.*		Marinov *et al.*	
Factors	T1	T2	T1	T2
Size of the food source	60	100	20	100
Limit	100	200	200	200
Iteration number	2500	1500	2500	1500
Crossover rate	0.1	0.1	0.5	0.1

its boundaries by (10). The counter for the new food source is also cleared as well. The steps of employed bees, onlooker bees, crossover and scout bees are repeated until the termination conditions are met. The program terminates if minimum cost is less than 0.01 and iteration number is greater than the maximum iteration predefined after sub-experiments.

In h-ABC algorithm, 4 design factors and 3 levels of each factor are taken as follows;

CONTROL FACTORS	LEVEL-3		
(A) Size of food source	20	60	100
(B) Limit	50	100	200
(C) Iteration number	500	1500	2500
(D) Crossover rate	0.1	0.3	0.5

L9 orthogonal array is constructed. There are 9 different experiments and each experiment is simulated 30 times independently. Calculating the average error, the best cases of control parameters in each experiment are set for h-ABC algorithm, and they are given as shown in Table 4.

B. GENETIC ALGORITHM

Genetic algorithms were introduced by John Holland [44]. In GA, we begin generating a population which consists of chromosomes randomly and evaluate fitness of the initial population by (11). Each gene of the chromosomes corresponds to a model parameter. Termination rules are checked for the initial population. If they are not met, the first generation begins with selection process. Population is sorted according to the highest fitness. Then one half of the population is kept, and the other one is deleted. Selection of parents for crossover is conducted by roulette wheel selection method and the offspring are produced by arithmetic crossover (13). Population is kept constant by placing the new offspring in empty positions. After crossover process is done, relatively small amount of mutation according to population size is introduced to population except the best chromosome. New population is evaluated again, and termination rules are checked. If these rules are satisfied the program terminates, otherwise generation number is increased by 1 and selection, crossover and mutation operations are repeated until termination rules are met. We define two termination rules. If minimum cost is less than 0.01 and generation counter is greater than the predefined maximum generation, the program terminates.

TABLE 5. The control parameters of genetic algorithm to set up.

	OFET Compact Models			
	Estrada *et al.*		Marinov *et al.*	
Factors	T1	T2	T1	T2
Mutation rate	0.1	0.1	0.3	0.2
Crossover probability	0.7	0.8	0.9	0.9
Population size	200	100	200	100
Generation number	1000	750	750	1000

The control parameters are effective on the performance of GA. Population size is one of them. If it is selected very small, sampling will not be enough for most hyperplanes. Larger population size provides many solutions in the search space and it reduces early convergence to local solutions. However, the number of evaluations per generation increases with the possible cost of slow convergence. Crossover operator is useful for convergence of population to the solutions. If it is higher new chromosomes are produced quickly, and it makes the algorithm converge faster. Too high crossover rate can disrupt the solutions before the selection can achieve any improvement. If it is selected too low the search becomes stationary. Mutation is a divergence operator. If the algorithm got stuck in a local minimum/maximum, a few mutations in the population can help to get out of that local solutions. On the other hand, higher number of mutations make the search purely random. For the selection operator, elitist strategy is followed that the best chromosome is remained unchanged through next generations.

In genetic algorithm 4 different control parameters are taken as design factors and their levels are chosen as 3.

CONTROL FACTORS	LEVEL-3		
(A) Mutation rate	0.1	0.2	0.3
(B) Crossover probability	0.9	0.8	0.7
(C) Population size	50	100	200
(D) Generation number	500	750	1000

Considering 4 design factors and 3 different levels for each factor, L9 orthogonal array can be constructed. There are 9 different experiments. After running each experiment 30 times independently, the average error is calculated, and best experiment is determined. The best experiment gives us the best values of the control parameters for our case. Hence, these control factors are set as in Table 5.

C. BACTERIAL FORAGING OPTIMIZATION ALGORITHM

Foraging strategies are determinant to survive in nature. As the weak ones are becoming extinct, the strongest ones are going to be transferred from generation to generation. These foraging strategies are considered as an optimization process by scientists. For instance, the foraging activity of

E. Coli bacteria is the inspiration to Kevin M. Passino and this activity is modelled in steps of chemotaxis, swarming, reproduction, elimination and dispersal [31].

1) CHEMOTAXIS

Chemotaxis is the action plan for bacteria including how to reach nutrients and how to escape from undesirable environments by swimming or tumbling. Moving in the same direction or changing the direction is achieved by swimming and tumbling, respectively. Chemotaxis is modelled mathematically as shown below:

$$\theta^{i}(j+1,k,l)=\theta^{i}(j,k,l)+C(i)\frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}} \tag{14}$$

where $\theta^{i}(j,k,l)$ symbolizes the ith bacterium at jth chemotactic, kth reproductive, and lth elimination and dispersal step; $C(i)$ is the run length unit which refers to the step size taken by the tumble in the random direction; $\Delta(i)$ is an arbitrary vector whose elements lie in $[-1, 1]$.

$$C(i)_k=\emptyset_{ss}\times\left(\frac{\Delta x_k}{\sqrt{n}}\right),\quad k=1,\ldots,n \tag{15}$$

where Δx_k is the distance between the lower and upper limits of each parameter; n is the number of parameters to be optimized; $\emptyset_{ss}\in[0,1]$ is a scaling factor for adjusting step size.

2) SWARMING

E. coli bacteria have an interesting communication network. When an optimal environment is discovered they stimulate each other chemically. They form concentric, dense patterns of groups and move together [31]. Swarming behavior can be performed by following mathematical equation.

$$\begin{aligned}&J_{cc}(\theta,P(j,k,l))\\&=\sum\nolimits_{i=1}^{S}J_{cc}^{i}\left(\theta,\theta^{i}(j,k,l)\right)\\&=\sum_{i=1}^{S}\left[-d_{attract}\exp\left(-w_{attract}\sum_{m=1}^{p}\left(\theta_m-\theta_m^{i}\right)^2\right)\right]\\&\quad+\sum\nolimits_{i=1}^{S}\left[h_{repellant}\exp\left(-w_{repellant}\sum_{m=1}^{p}\left(\theta_m-\theta_m^{i}\right)^2\right)\right]\end{aligned} \tag{16}$$

where $J_{cc}(\theta,P(j,k,l))$ is the cost function value to be added to the actual cost function to be minimized. It presents a time-varying cost function. 'S' is the total bacteria number, 'p' is the number of parameters to be optimized and $\theta=\left[\theta_1,\theta_2,\ldots,\theta_p\right]^T$ is a point in the search space. $d_{attract}$, $w_{attract}$, $h_{repellent}$, $w_{repellent}$ are significant coefficients to be set carefully. If there is no swarming effect $J_{cc}(\theta,P(j,k,l))$ is taken as 0.

3) REPRODUCTION

When the chemotaxis process is completed, health values of bacteria are sorted. The least healthy half of bacteria are removed, and each one of the bacteria in the other half is split into two bacteria. The new bacteria are placed in the location of the removed ones. Thereby the population of bacteria remains constant.

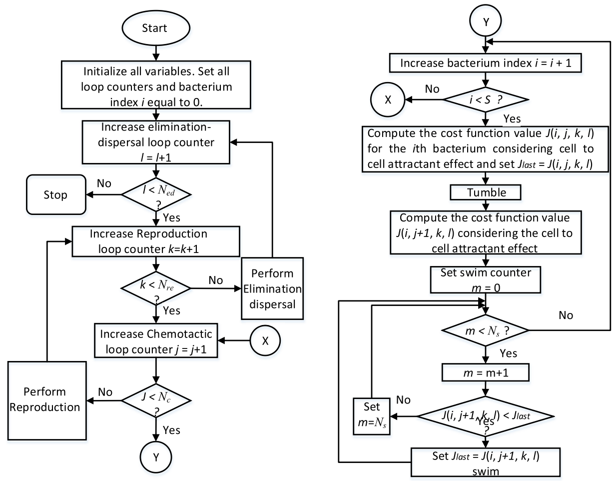

FIGURE 3. The flowchart of the BFO algorithm.

4) ELIMINATION AND DISPERSAL

Running short of nutrients, severe temperature variations can affect the bacteria population. This effect can be elimination of the whole group or dispersion of them to a new environment. In this process chemotaxis can be destroyed but possibly it can also be improved to find better locations. Each bacterium is subjected to elimination and dispersal process with probability P_{ed}. This process avoids being trapped in local optima.

Flowchart of the BFO algorithm is given in Fig.3 and the pseudo code of it can be examined in [45]. In brief, BFO algorithm begins by the process of initialization. Elimination-dispersal, reproduction and chemotaxis loops are labeled from outer loop to inner loop. In chemotaxis loop, a chemotactic step is taken for each bacterium and cost function is evaluated. If there is swarming, (16) is calculated and summed with the actual cost otherwise J_{cc} is taken as 0. The best cost is stored until finding a better cost. In tumbling process, random $\Delta(i)$ vector is produced and (14) is calculated. Here, cost function is evaluated again, and swimming step begins. If there is improvement in cost then swimming counter is increased, otherwise swimming is terminated, and next bacterium is taken for evaluations. After chemotactic step, the best half of bacteria remain in the population and each bacterium split into two bacteria. After reproduction loop is completed, elimination-dispersal step is processed with the P_{ed} probability. If a bacterium is eliminated, another one is dispersed to a random location. BFO algorithm terminates after getting out of elimination-dispersal loop. If minimum cost is less than 0.01 in nested loops, the program also terminates.

In BFO algorithm, parameter choices are very important to get well performance from the algorithm.

TABLE 6. The control parameters of BFO algorithm to set up.

	OFET Compact Models			
	Estrada *et al.*		Marinov *et al.*	
Factors	T1	T2	T1	T2
S	50	50	40	50
N_c	30	30	20	10
N_s	5	5	10	20
N_{re}	25	25	25	15
N_{ed}	2	2	3	3
P_{ed}	0.1	0.1	0.1	0.1
$\emptyset_{ss}$	0.01	0.01	0.005	0.01

Passino gives guidelines to choose these parameters in [31]. Large bacteria population may give us solutions near optimum, but it increases computational complexity. As too small step sizes can cause slow convergence, larger steps may cause missing the local minima. Larger chemotactic steps mean more optimization process with the cost of higher computational complexity. For very short chemotactic steps, algorithm can be trapped in local minima and search will depend on luck and reproduction. The swimming length improves the convergence ability. If reproduction is too small premature convergence may occur; however larger values of reproduction bring higher computational cost. Another control parameter is elimination-dispersal events count and lower values of this parameter mean less dependence of the elimination-dispersal event. Finally choosing a proper probability value for elimination-dispersal will help the algorithm escaping from local optima to global one. Indeed, it is an optimization problem as well.

In BFO algorithm, 7 different control factors and 3 levels of each factor are taken.

CONTROL FACTORS	LEVEL-3		
(A) Bacteria population (S)	30	40	50
(B) Chemotactic steps count (N_c)	10	20	30
(C) The length of swimming (N_s)	5	10	20
(D) Reproduction steps count (N_{re})	5	15	25
(E) Elimination-dispersal events count (N_{ed})	1	2	3
(F) The probability of Elimination-dispersal (P_{ed})	0.1	0.2	0.3
(G) Step size ratio ($\emptyset_{ss}$)	0.005	0.01	0.02

L18 orthogonal array is constructed to design experiments of BFO algorithm. 18 different experiments are simulated 30 times independently and average error is calculated. The best cases of control parameters in each experiment are set for BFO algorithm, and they are given as shown in Table 6.

IV. RESULTS

The metaheuristics-based optimization algorithms such as genetic, h-ABC and BFO algorithms are applied to extract model parameters for I-V measurements of T1 data from [46] and T2 data from the fabricated transistor in our laboratory.

TABLE 7. OFETs' constant parameters for simulations.

Transistor	W (μm)	L (μm)	C_i (nF/cm^2)
T1	100	10	700
T2	1000	20	10.9

TABLE 8. Extracted OFET Model Parameters for the model of Estrada *et al.*

#	Method	μ_0 (cm^{2}V^{-1}s^{-1})	V_T (V)	γ	V_{AA} (V)	R (kΩ)	α_s	m	λ (V^{-1})	NRMSE %
T1	h-ABC	0.855	-0.985	0.88	3.27	98.3	0.559	3.08	1.11E-4	3.29
	BFO	0.748	-1.008	0.78	3.16	90.6	0.563	3.12	1.65E-3	3.54
	GA	0.789	-1.030	0.68	3.84	81.6	0.569	3.09	1.33E-3	3.70
	Method in [16]	1	-1.169	0.16	1071	3.8	0.552	3.64	2.99E-2	6.94
T2	h-ABC	0.550	-1.495	0.96	5363	480.8	0.567	3.90	1.84E-3	2.66
	BFO	0.618	-1.982	0.93	6969	483.8	0.556	3.85	3.23E-3	2.88
	GA	0.638	-1.663	0.99	5091	1014	0.551	3.98	3.01E-3	2.95
	Method in [16]	1	-2.821	0.83	23340	32.9	0.571	4.75	3.66E-2	6.79

Some physical parameters of the transistors are given in Table 7.

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 [46]. 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.

In h-ABC algorithm the size of food source, the number of employed and onlooker bees and the other control parameters are given in section III-A and discussed. In GA, the control parameters of GA such as population size, maximum generation number, crossover probability, and mutation rate are selected as shown in section III-B after a series of experiments and discussed. In BFO algorithm, the choices of S, N_c, N_s, N_{re}, N_{ed}, P_{ed}, and $\emptyset_{ss}$ are very important for faster convergence near to the global optima. These control parameters are given in section III-C and discussed. In this work, we do not consider the swarming effect, because it adds J_{cc} to the actual cost and we want to keep consistency of the costs to compare with other algorithms.

A. MODEL BY ESTRADA ET AL.

Equation (2) consists of all the parameters to be extracted and it is used for the parameter extraction process. Experimental and calculated transfer characteristic curves are shown in Fig. 4a, and Fig. 4c as well as output characteristic curves are shown in Fig. 4b, and Fig. 4d. Transfer characteristics of

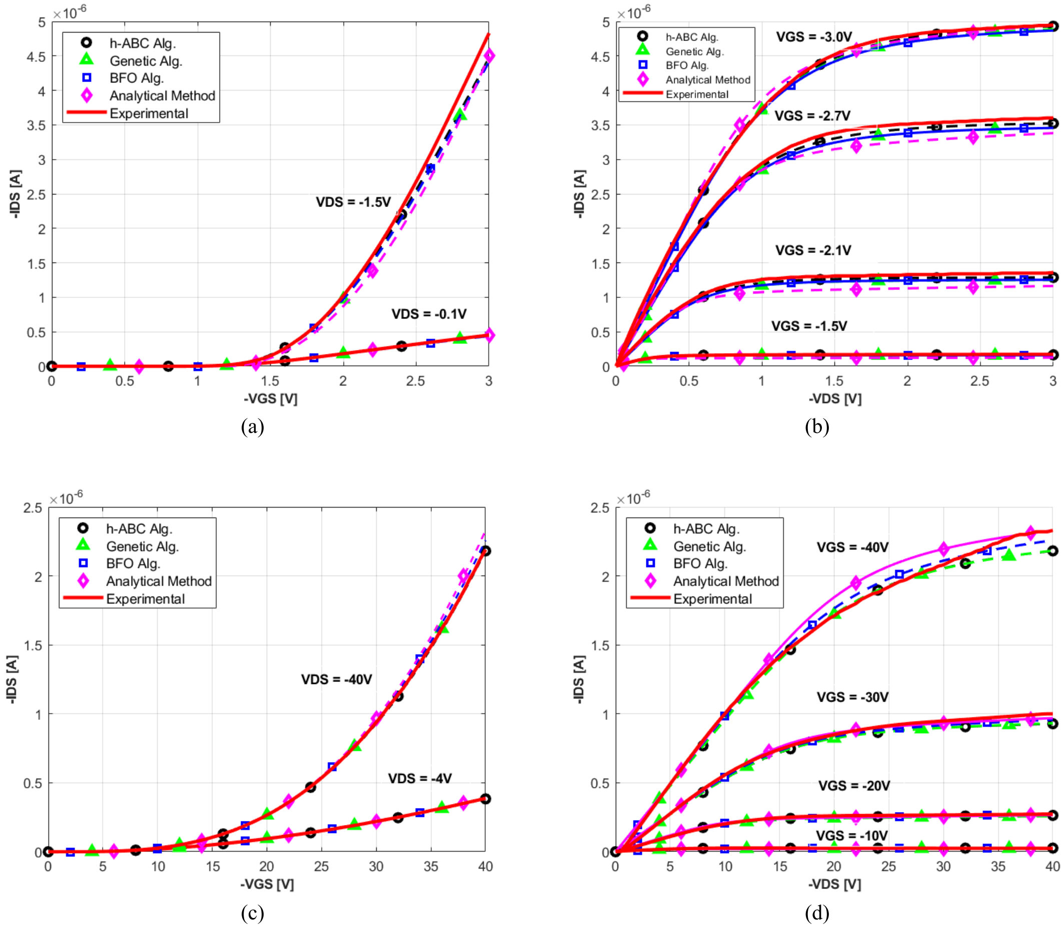

FIGURE 4. a) Transfer Characteristic Curves of T1 for Estrada's Model. b) Output Characteristic Curves of T1 for Estrada's Model. c) Transfer Characteristic Curves of T2 for Estrada's Model. d) Output Characteristic Curves of T2 for Estrada's Model.

T1 are calculated with -0.1V and -1.5V values of V_{DS}, and transfer characteristics of T2 are calculated with -4V and -40V values of V_{DS}, respectively. Direct extraction method is also applied to data of transfer and output characteristics as given in [16]. Extracted model parameters by genetic, h-ABC and BFO algorithms, and the direct extraction method are given in Table 8 for both T1 and T2. Parameter values are calculated by taking average of them after 30 independent runs and it is necessary to remind here that modelled curves are plotted with these average parameters. Average error performances of metaheuristics are below 3.70% and 2.95% for T1 & T2, respectively. On the other hand, they are 6.94% and 6.79% for the direct extraction method, respectively. It is obvious that the proposed metaheuristics-based approach performs better than the direct one. The model equation of Estrada *et al.* is simulated with extracted parameters to predict output characteristic curves. As shown in Fig. 4b and Fig. 4d, predicted curves can closely follow the experimental data. If we examine the model parameters in Table 8, it is seen that parameters are consistent with each other except some parameters. For example, γ and V_{AA} parameters vary a lot according to the used method and/or device. In direct extraction method band mobility is taken as 1 $\mathrm{cm^2V^{-1}s^{-1}}$ as a default value and these two empirical parameters adjust the field effect mobility. After calculating field effect mobility from (1) at maximum V_{GS}, μ_{FET} is found as 0.36 — 0.56 $\mathrm{cm^2V^{-1}s^{-1}}$ for T1 and 0.0048 — 0.0051 $\mathrm{cm^2V^{-1}s^{-1}}$ for T2. In [46], carrier mobility and threshold voltage are given as 0.4 $\mathrm{cm^2V^{-1}s^{-1}}$ and -1.2V for T1 OFET device, respectively. Thus, we see that even variations in γ and V_{AA} are a lot, calculated μ_{FET} values are consistent. We observe variations in V_T and authors say that severe V_T shifts can be observed especially in room temperature due to bias voltages [14]. In (2), V_T is taken as a constant parameter and V_T shifts are not modeled. Under these conditions variations in threshold voltage is expected for us and we discussed these variations in details for Marinov's model in the next subsection as well. The authors also give contact and channel resistance values in [46]. Contact resistance is between 85$k\Omega$ and 120$k\Omega$, and channel resistance between 130$k\Omega$ and 180$k\Omega$ for linear and saturation regimes. These parameters are really close to extracted R parameters in Table 8 for T1; and resistance values are higher in T2 as we expected because T2 has bottom-gate, bottom contact structure. As stated in [46], top contact structures are advantageous for smaller contact resistance. T2 transistor has lower mobility and lower oxide capacitance values, hence it needs higher operating voltages to produce similar current values. Parameter m controls the sharpness of transition from linear regime to saturation regime. As seen in Table 8, m value extracted by the method in [16] is 3.64 for T1 and 4.75 for T2 and other optimized values are also close to 3 and 4 for T1 and T2, respectively. Besides, parameter α_s determines the saturation voltage and the extracted parameter values are found in the range of 0.55 — 0.57 for both transistors. These parameter values offer smooth transitions of the output curves with relatively low fitting error values. However the error is found high for the direct extraction method in [16]. This method extracts parameters step by step and they are obviously not optimum values. On the other hand, metaheuristics-based approach extracts all parameters at once and they are close to the optimum values providing less error. Another reason for higher error of direct extraction method is channel length modulation parameter λ that is extracted for maximum values of V_{GS} and V_{DS} in this method and its value is inappropriately higher compared to the metaheuristics-based methods for both OFETs. Looking at output characteristic curves we are satisfied with performance of the proposed parameter extraction approach. Although the direct extraction methods do a good job too, the extracted parameters are less precise, and the error is higher between actual and predicted current values; they also need human assistance. Metaheuristics-based approach can be simply adapted for another OFET model by defining model equations and parameters.

B. MODEL BY MARINOV ET AL.

After showing good performance of the proposed parameter extraction approach using metaheuristics for model of Estrada *et al.*, its performance is tested for another model. The direct extraction method in previous section is presented for (2); hence it's all steps are not applicable for the model of Marinov *et al.* Therefore we use the method introduced in [33]. In this method γ and V_T are extracted by a technique so-called H_{VG} function from the saturation regime. Another parameter of subthreshold slope voltage V_{SS} is extracted with the practical rule given in [33] (see eq. 7), V_{AA} parameter is taken as 1V and only the low field mobility μ_0 is adjusted to fit the measurement. Finally, channel length modulation parameter λ is calculated for maximum V_{GS} and V_{DS} as in [16]. Results are given in Table 9.

As the last case of parameter extraction simulations bacterial foraging, genetic and h-ABC optimization algorithms are once again applied to the model of Marinov *et al.* The authors published more complicated compact model including some other effects. However, drain current equation (9) of the core model is used to extract parameters for T1 and T2 transistors in this case. In (9) there are 6 model parameters as given in Table 1. The constant technology parameters are as shown in Table 7. First, data of T1 and T2 transistors and the equation of Marinov *et al.* are given to the parameter extractor and results are tabulated in Table 9. Transfer characteristic curves of T1 are produced for $V_{DS} = -0.1$V and $V_{DS} = -1.5$V and transfer characteristics of T2 are produced for $V_{DS} = -4$V and $V_{DS} = -40$V, respectively and it is very successful for all algorithms as shown in Fig.5a and Fig.5c. Calculated errors are below 8.74% for T1 and below 6.97% for T2 for three metaheuristics. After the model parameters are extracted, this model equation is simulated to predict output transfer curves of both transistors. Four output curves for T1 using gate voltages of −1.5V, −2.1V, −2.7V and −3V; four output curves for T2 under gate bias voltages of −10V, −20V, −30V, and −40V are produced by the model as shown in Fig. 5b and Fig. 5d and they are plotted with measured data on the same plot for comparison. It seems that the model equation captures the behavior of output characteristics for both OFETs. Field effect mobility, μ_{FET}, is found as 0.36 — 0.37 $cm^2V^{-1}s^{-1}$ for T1 and 0.0048 — 0.005 $cm^2V^{-1}s^{-1}$ for T2, calculating field effect mobility from (1) at maximum V_{GS}. Critical parameters like field effect mobility and threshold voltage are consistent with [46] as given in section IV-A. Note that mobility and threshold voltage values vary in our results and it is expected that these parameters vary with bias [33]. It is especially necessary to remind that the operating voltage is ±40V for T2. Threshold voltage values are in the range of ±10% of the mean. As discussed in [33], the dependency of V_T and V_{DS} can be denoted and effective threshold voltage can be included in the model. It is stated that this modification can be justified physically according to variation of quasi-Fermi level [36]. However, this empirical modification causes problems and tradeoffs are necessary among model parameters [33]. As seen in Table 9, parameters of γ and V_{AA} vary a lot as well. These parameters are fitting parameters just to adjust field effect mobility in Marinov's model too. Although V_{AA} parameter seems unphysical, calculated field effect mobility values by (1) are reasonable. Extracted V_{SS} parameters seem physically consistent. The direct extraction method and other metaheuristics-based methods extract

TABLE 9. Extracted OFET Model Parameters for the model of Marinov et al.

#	Method	μ_0 ($cm^2V^{-1}s^{-1}$)	V_T (V)	V_{SS}	V_{AA} (V)	γ	λ (V^{-1})	NRMSE %
T1	h-ABC	0.506	-0.999	0.119	6.40	0.284	5.16E-2	7.19
	BFO	0.377	-1.220	0.222	7.05	0.004	7.86E-2	6.68
	GA	0.423	-1.021	0.243	6.11	0.128	9.53E-3	8.74
	Method in [33]&[16]	0.357	-1.169	0.124	1	0.16	4.85E-2	9.17
T2	h-ABC	0.695	-2.993	0.635	36360	0.715	1.59E-2	6.00
	BFO	0.792	-2.502	0.592	26670	0.776	1.61E-2	5.98
	GA	0.615	-2.489	0.784	60540	0.656	1.55E-2	6.97
	Method in [33]&[16]	2.42E-4	-2.821	0.685	1	0.83	1.82E-2	8.67

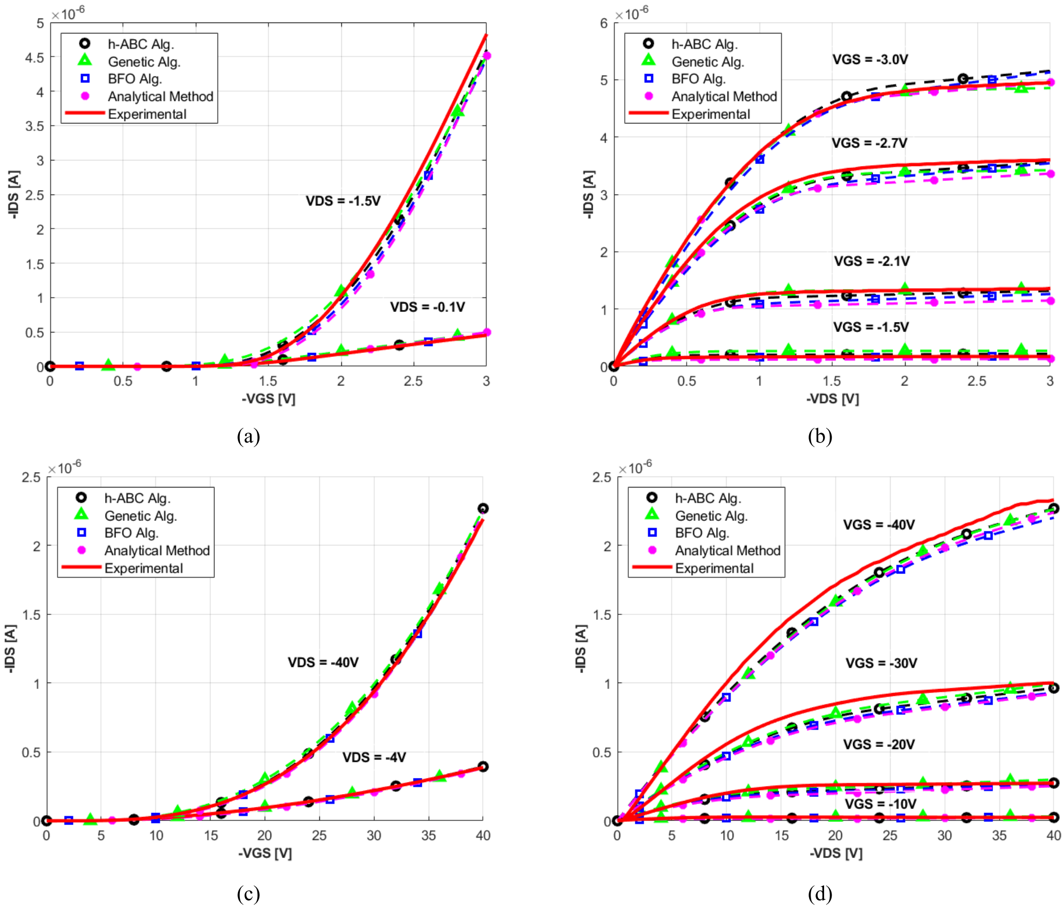

FIGURE 5. a) Transfer Characteristic Curves of T1 for Marinov's Model. b) Output Characteristic Curves of T1 for Marinov's Model. c) Transfer Characteristic Curves of T2 for Marinov's Model. d) Output Characteristic Curves of T2 for Marinov's Model.

similar values of V_{SS} for both transistors. In [36] subthreshold swing (SS) is given as 100 mV/dec for T1 and our results are between 112 — 243 mV/dec for T1. The direct extraction method and h-ABC algorithms find the closest two values to 100 mV/dec as 124mV/dec and 119 mV/dec, respectively. The model equation of Marinov *et al.* lacks parameters such as m and α_s. These parameters are helpful for smooth transition in output curves. We think that that's why its simulation performance is lower than the model equation of Estrada *et al.* However, Marinov *et al.* stated in [15] that they excluded these parameters deliberately. They noted that m parameter caused physically unrealistic negative values for the channel length modulation parameter and α_s parameter was redundant. We agree that variations in m parameter for some instances can cause negative λ parameter but extracted values of α_s are meaningful for our experiments as seen in Table 9.

On the other hand, because the model equations are not very complicated performances of the metaheuristic algorithms have not much significant difference. However, our primary concern is introducing power of metaheuristics to the parameter extractor in this work, not to compare them. Nevertheless, if we hit on average performances of algorithms h-ABC and BFO algorithms perform better than GA in each case as we expected. Taguchi's OED method is very helpful tuning the control parameters of algorithms. After tuning the control parameters, optimization performance of the metaheuristics is very good as we expected. The choice of control parameters affects the computation time a lot and instead of comparing their computation times we interest in finding an optimal choice for the control parameters. However, we perform an experiment to give some insight about computation times. And results are given in Table 9. We use MATLAB 2018a on an Intel Core i7-4790 CPU @ 3.60 GHz computer with 8 GB RAM and Windows 10 Pro 64 Bit. We use the best average NRMSE values given in Table 8 and Table 9 as targets for each case and we run algorithms until they reach these targets. Termination time is defined as 300 seconds. For example, the best NRMSE value is 3.29% for T1 and the model of Estrada *et al.*, hence the target is 3.29% for each algorithm. In this example, while h-ABC algorithm reaches the target in 60s, BFO algorithm reaches the target in 91s. However, GA cannot reach the target in 300s and this situation is indicated as NA in Table 10. It is seen in Table 10 that h-ABC and BFO algorithms perform better than GA as we expected. Whereas BFO algorithm performs better for

TABLE 10. Computation times of algorithms for each model and OFET.

	Computation Times (in sec.)					
	T1			T2		
	GA	h-ABC	BFO	GA	h-ABC	BFO
Estrada *et al.*	NA	60	91	248	95	127
Marinov *et al.*	NA	41	34	122	36	29

the model of Marinov *et al.*, h-ABC algorithm is better for the model of Estrada *et al.* We think that h-ABC algorithm outperforms when the number of parameters increases, and we take it as a lesson for future works.

As a last remark, the proposed metaheuristics-based parameter extraction approach works very well with the studied OFET compact models and transistors; and it can also be applied to other OFET compact models simply adapting the model equations.

V. CONCLUSION

Parameter extraction approach based on metaheuristics of h-ABC, BFO and genetic algorithms is implemented on two different compact models for two different datasets of OFETs (T1&T2) both having pentacene active layer in this work. First, it is shown that the proposed metaheuristics-based approach is more precise than the compared direct extraction method for the model of Estrada *et al.* After that its applicability to another OFET compact model of Marinov *et al.* is validated. Four cases are simulated for each algorithm, and the studied OFET compact models with extracted parameters can fit to experimental characteristic curves successfully. Considering average performances, BFO and h-ABC algorithms perform better comparing to genetic algorithm, because they do both local and global search and converge faster than GA. We also observe that h-ABC outperforms when the number of parameters increase, and we take it as a lesson for future works. The simulated model data show a good agreement with experimental data of T1 & T2, and the compact model by Estrada *et al.* performs better compared to the model of Marinov *et al.* This is mostly because more parameters are used in the compact model by Estrada *et al.*

Our primary target is building robust and accurate compact models for different device structures and organic materials. Therefore, we will have experiments with different materials and device structures and will collect data to develop more comprehensive OFET compact model for future works. We will research the effect of contact materials, bias stresses and temperature. We will also continue improving our metaheuristics-based parameter extractor to have more accurate parameters.

REFERENCES

[1] Y. S. Rim, S.-H. Bae, H. Chen, N. De Marco, and Y. Yang, "Recent progress in materials and devices toward printable and flexible sensors," *Adv. Mater.*, vol. 28, no. 22, pp. 4415–4440, 2016.

[2] J. Yang, Z. Zhao, S. Wang, Y. Guo, and Y. Liu, "Insight into high-performance conjugated polymers for organic field-effect transistors," *Chem*, vol. 4, no. 12, pp. 2748–2785, 2018.

[3] X. Gao and Z. Zhao, "High mobility organic semiconductors for field-effect transistors," *Sci. China Chem.*, vol. 58, no. 6, pp. 947–968, 2015.

[4] S. Casalini, C. A. Bortolotti, F. Leonardi, and F. Biscarini, "Self-assembled monolayers in organic electronics," *Chem. Soc. Rev.*, vol. 46, no. 1, pp. 40–71, 2017.

[5] C. Wang, C. Wang, Z. Huang, and S. Xu, "Materials and structures toward soft electronics," *Adv. Mater.*, vol. 30, no. 50, 2018, Art. no. 1801368.

[6] B. Kumar, B. K. Kaushik, and Y. S. Negi, "Organic thin film transistors: Structures, models, materials, fabrication, and applications: A review," *Polym. Rev.*, vol. 54, no. 1, pp. 33–111, 2014.

[7] R. M. Meixner, H. H. Gobel, H. Qiu, C. Ucurum, W. Klix, R. Stenzel, F. A. Yildirim, W. Bauhofer, and W. H. Krautschneider, "A physical-based PSPICE compact model for poly(3-hexylthiophene) organic field-effect transistors," *IEEE Trans. Electron Devices*, vol. 55, no. 7, pp. 1776–1781, Jul. 2008.

[8] B. Iñiguez, R. Picos, D. Veksler, A. Koudymov, M. S. Shur, T. Ytterdal, and W. Jackson, "Universal compact model for long- and short-channel thin-film transistors," *Solid. State. Electron.*, vol. 52, no. 3, pp. 400–405, 2008.

[9] M. Estrada, I. Mejía, A. Cerdeira, J. Pallares, L. F. Marsal, and B. Iñiguez, "Mobility model for compact device modeling of OTFTs made with different materials," *Solid-State Electron.*, vol. 52, no. 5, pp. 787–794, 2008.

[10] S. Mijalković, D. Green, A. Nejim, A. Rankov, E. Smith, T. Kugler, C. Newsome, and J. Halls, "UOTFT: Universal organic TFT model for circuit design," ină*Proc. Int. Conf. Organic Electron.*, 2009, p. 2.

[11] L. Li, M. Debucquoy, J. Genoe, and P. Heremans, "A compact model for polycrystalline pentacene thin-film transistor," *J. Appl. Phys.*, vol. 107, no. 2, 2010, Art. no. 24519.

[12] F. Torricelli, K. O'Neill, G. H. Gelinck, K. Myny, J. Genoe, and E. Cantatore, "Charge transport in organic transistors accounting for a wide distribution of carrier energies—Part II: TFT modeling," *IEEE Trans. Electron Devices*, vol. 59, no. 5, pp. 1520–1528, May 2012.

[13] C. H. Kim, A. Castro-Carranza, M. Estrada, A. Cerdeira, Y. Bonnassieux, G. Horowitz, and B. Iniguez, "A compact model for organic field-effect transistors with improved output asymptotic behaviors," *IEEE Trans. Electron Devices*, vol. 60, no. 3, pp. 1136–1141, Mar. 2013.

[14] M. Estrada, A. Cerdeira, J. Puigdollers, L. Reséndiz, J. Pallares, L. F. Marsal, C. Voz, and B. Iñiguez, "Accurate modeling and parameter extraction method for organic TFTs," *Solid-State Electron.*, vol. 49, no. 6, pp. 1009–1016, 2005.

[15] O. Marinov, M. J. Deen, U. Zschieschang, and H. Klauk, "Organic thin-film transistors: Part I—Compact DC modeling," *IEEE Trans. Electron Devices*, vol. 56, no. 12, pp. 2952–2961, Dec. 2009.

[16] L. Reséndiz, M. Estrada, and A. Cerdeira, "New procedure for the extraction of a-Si:H TFTs model parameters in the subthreshold region," *Solid. State. Electron.*, vol. 47, no. 8, pp. 1351–1358, 2003.

[17] C.-H. Kim, Y. Bonnassieux, and G. Horowitz, "Compact DC modeling of organic field-effect transistors: Review and perspectives," *IEEE Trans. Electron Devices*, vol. 61, no. 2, pp. 278–287, Feb. 2014.

[18] I. Benacer and Z. Dibi, "Extracting parameters of OFET before and after threshold voltage using genetic algorithms," *Int. J. Autom. Comput.*, vol. 13, no. 4, pp. 382–391, 2016.

[19] B. Yaglioglu, T. Agostinelli, P. Cain, S. Mijalkovic, and A. Nejim, "Parameter extraction and evaluation of UOTFT model for organic thin-film transistor circuit design," *J. Display Technol.*, vol. 9, no. 11, pp. 890–894, Nov. 2013.

[20] S. Jung, J. W. Jin, V. Mosser, Y. Bonnassieux, and G. Horowitz, "A compact model and parameter extraction method for a staggered OFET with power-law contact resistance and mobility," *IEEE Trans. Electron Devices*, vol. 66, no. 11, pp. 4894–4900, Nov. 2019.

[21] Y. H. Hu and S. Pan, "SaPOSM: An optimization method applied to parameter extraction of MOSFET models," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, vol. 12, no. 10, pp. 1481–1487, Oct. 1993.

[22] T. Sakurai, B. Lin, and A. R. Newton, "Fast simulated diffusion: An optimization algorithm for multiminimum problems and its application to MOSFET model parameter extraction," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, vol. 11, no. 2, pp. 228–234, Feb. 1992.

[23] T. Bendib and F. Djeffal, "Electrical performance optimization of nanoscale double-gate MOSFETs using multiobjective genetic algorithms," *IEEE Trans. Electron Devices*, vol. 58, no. 11, pp. 3743–3750, Nov. 2011.

[24] F. Djeffal and T. Bendib, "Multi-objective genetic algorithms based approach to optimize the electrical performances of the gate stack double gate (GSDG) MOSFET," *Microelectron. J.*, vol. 42, no. 5, pp. 661–666, 2011.

[25] P. Moreno, R. Picos, M. Roca, E. Garcia-Moreno, B. Iniguez, and M. Estrada, "Parameter extraction method using genetic algorithms for an improved OTFT compact model," in *Proc. Spanish Conf. Electron Devices*, 2007, pp. 64–67.

[26] Y. Leung, Y. Gao, and Z.-B. Xu, "Degree of population diversity—A perspective on premature convergence in genetic algorithms and its Markov chain analysis," *IEEE Trans. Neural Netw.*, vol. 8, no. 5, pp. 1165–1176, Sep. 1997.

[27] A. Romero, J. González, R. Picos, M. J. Deen, and J. A. Jiménez-Tejada, "Evolutionary parameter extraction for an organic TFT compact model including contact effects," *Organic Electron.*, vol. 61, pp. 242–253, Oct. 2018.

[28] S. Fatima, U. Rafique, U. F. Ahmed, and M. M. Ahmed, "A global parameters extraction technique to model organic field effect transistors output characteristics," *Solid-State Electron.*, vol. 152, pp. 81–92, Feb. 2019.

[29] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Appl. Soft Comput.*, vol. 8, pp. 687–697, Jan. 2008.

[30] S. L. Sabat, S. K. Udgata, and A. Abraham, "Artificial bee colony algorithm for small signal model parameter extraction of MESFET," *Eng. Appl. Artif. Intell.*, vol. 23, no. 5, pp. 689–694, 2010.

[31] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," *IEEE Control Syst. Mag.*, vol. 22, no. 3, pp. 52–67, Mar. 2002.

[32] S. Mishra and C. N. Bhende, "Bacterial foraging technique-based optimized active power filter for load compensation," *IEEE Trans. Power Del.*, vol. 22, no. 1, pp. 457–465, Jan. 2007.

[33] M. J. Deen, O. Marinov, U. Zschieschang, and H. Klauk, "Organic thin-film transistors: Part II—Parameter extraction," *IEEE Trans. Electron Devices*, vol. 56, no. 12, pp. 2962–2968, Dec. 2009.

[34] J. Li and R. S. K. Kwan, "A fuzzy simulated evolution algorithm for the driver scheduling problem," in *Proc. Congr. Evol. Comput.*, vol. 2, May 2001, pp. 1115–1122.

[35] G. Taguchi, *Introduction to Quality Engineering: Designing Quality into Products and Processes*. Tokyo, Japan: Asian Productivity Organization, 1986.

[36] M. Shur and M. Hack, "Physics of amorphous silicon based alloy field-effect transistors," *J. Appl. Phys.*, vol. 55, no. 10, pp. 3831–3842, May 1984.

[37] M. C. J. M. Vissenberg and M. Matters, "Theory of the field-effect mobility in amorphous organic transistors," *Phys. Rev. B, Condens. Matter*, vol. 57, pp. 12964–12967, May 1998.

[38] M. Ahmed, "Optimisation of tool wear and cutting forces on the basis of different cutting parameters," *Int. J. Adv. Res. Innov. Ideas Educ*, vol. 3, no. 1, pp. 613–626, 2017.

[39] Y. Liu, X. Ling, Y. Liang, and G. Liu, "Improved artificial bee colony algorithm with mutual learning," *J. Syst. Eng. Electron.*, vol. 23, no. 2, pp. 265–275, Apr. 2012.

[40] S. Dasgupta, S. Das, A. Abraham, and A. Biswas, "Adaptive computational chemotaxis in bacterial foraging optimization: An analysis," *IEEE Trans. Evol. Comput.*, vol. 13, no. 4, pp. 919–941, Aug. 2009.

[41] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Erciyes Univ., Kayseri, Turkey, Tech. Rep. TR06, 2005, p. 10.

[42] L. Ma, Y. Zhu, D. Zhang, and B. Niu, "A hybrid approach to artificial bee colony algorithm," *Neural Comput. Appl.*, vol. 27, no. 2, pp. 387–409, 2016.

[43] S. S. Jadon, R. Tiwari, H. Sharma, and J. C. Bansal, "Hybrid artificial bee colony algorithm with differential evolution," *Appl. Soft Comput.*, vol. 58, pp. 11–24, Sep. 2017.

[44] J. H. Holland, *Adaptation in Natural and Artificial Systems*. Cambridge, MA, USA: MIT Press, 1992.

[45] S. Das, A. Biswas, S. Dasgupta, and A. Abraham, "Bacterial foraging optimization algorithm: Theoretical foundations, analysis, and applications," in *Foundations of Computational Intelligence*, vol. 3, A. Abraham, A. E. Hassanien, P. Siarry, and A. Engelbrecht, Eds. Berlin, Germany: Springer, 2009, pp. 23–55.

[46] H. Klauk, U. Zschieschang, and M. Halik, "Low-voltage organic thin-film transistors with large transconductance," *J. Appl. Phys.*, vol. 102, no. 7, 2007, Art. no. 74514.

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