Design of a Front–End Amplifier for the Maximum Power Delivery and Required Noise by HBMO with Support Vector Microstrip Model

Filiz GÜNEŞ, Salih DEMİREL, Peyman MAHOUTİ

Department of Electronics and Communication Engineering, Yıldız Technical University,
Davutpasa Campus, 34220, Istanbul, Turkey

gunes@yildiz.edu.tr, salihd@yildiz.edu.tr, pmahouti@gmail.com

Abstract. *Honey Bee Mating Optimization (HBMO) is a recent swarm-based optimization algorithm to solve highly nonlinear problems, whose based approach combines the powers of simulated annealing, genetic algorithms, and an effective local search heuristic to search for the best possible solution to the problem under investigation within a reasonable computing time. In this work, the HBMO-based design is carried out for a front-end amplifier subject to be a subunit of a radar system in conjunction with a cost effective 3-D SONNET-based Support Vector Regression Machine (SVRM) microstrip model. All the matching microstrip widths, lengths are obtained on a chosen substrate to satisfy the maximum power delivery and the required noise over the required bandwidth of a selected transistor. The proposed HBMO-based design is applied to the design of a typical ultra-wide-band low noise amplifier with NE3512S02 on a substrate of Rogers 4350 for the maximum output power and the noise figure F(f) = 1 dB within the 5-12 GHz using the T-type of microstrip matching circuits. Furthermore, the effectiveness and efficiency of the proposed HBMO based design are manifested by comparing it with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and the simple HBMO based designs.*

Keywords

Honey Bee Mating, Low Noise Amplifier, microstrip, optimization, matching circuit, SVRM.

1. Introduction

Considering all the stringent requirements which include high gain, low input and output Voltage Standing Wave Ratio (VSWR)'s, low noise figure together with the low-power consumption from the low-level battery, the wideband miniature Low Noise Amplifier (LNA) design is one of the biggest challenges to Ultra -Wideband (UWB) transceiver integrations. To meet these stringent requirements, first of all, fast and low-noise, high-quality transistors are needed. In fact, today's semiconductor technology has been focusing on producing the microwave transistors with the intrinsic superior frequency characteristics. Second issue is of course to establish the compromise interrelations among the power gain, the input/output VSWRs, the noise figure, the bias conditions (V_{DS}, I_{DS}) and frequency (f) of the two port transistor.

Recently, the nonlinear performance equations of the transistor are solved simultaneously with respect to the source impedance in the [z]-domain for the maximum power delivery and the required noise using the linear circuit and noise theories, by our research group to be used in the design of the front-end amplifier [1], [2]. Thus dependences of the maximum gain G_{Tmax} under the conjugate matched output is obtained on the rigorous mathematical bases with respect to the noise figure, input VSWR throughout operation domain (V_{DS}, I_{DS}, f).

On the other hand, one of the recently proposed nature inspired intelligence algorithms that have shown great potential and good perspective for the solutions of various difficult optimization problems is the HBMO [3-6]. The HBMO algorithm first proposed by Afshar et al. has been used to solve a single reservoir optimization problem [3], [4], clustering [5], state estimation in distribution networks [6].

In this work, we propose a HBMO design optimization procedure given in Fig. 1 for a front-end amplifier so that all the matching microstrip widths, lengths $\{\vec{W}, \vec{\ell}\}$ can be obtained to provide the (Z_S, Z_L) terminations on a given substrate (ε_r, h, $\tan\delta$) for the maximum power delivery and the required noise over the required bandwidth of a selected transistor, respectively. The HBMO procedure of the front-end amplifier design (Fig. 1) can be considered to be consisting of the following stages:

(i) Firstly, Feasible Design Target (FDT) is built by solving analytically [1], [2] or numerically the highly nonlinear performance equations of the transistor for the maximum power delivery and the required noise to determine the necessary source Z_S and load Z_L impedances of the active device at a chosen bias condition (V_{DS}, I_{DS}) of the device as follows:

$$Z_S(\omega_i) = r_S(\omega_i) + jx_S(\omega_i) \quad , \tag{1}$$

$$Z_L(\omega_i) = r_L(\omega_i) + jx_L(\omega_i) = Z^*_{out}(Z_S(\omega_i)) \quad , \tag{2}$$

where $$r_S(\omega_i) > 0,\ r_L(\omega_i) > 0,\ i = 1, ..., N \tag{3}$$

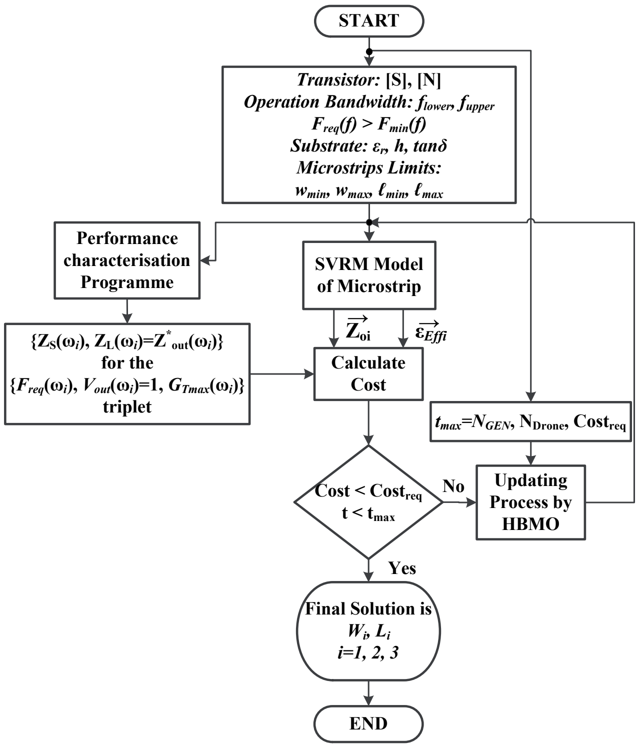

Fig. 1. Flow chart of the HBMO+SVRM design optimization procedure.

(ii) Second stage is the design optimization of the microstrip widths, lengths $\{\vec{W}, \vec{\ell}\}$ of the input/output matching circuits using the HBMO with the royal jelly, to provide the necessary source $Z_S(\omega_i)$ and load $Z_L(\omega_i)$ impedances, respectively to the device. Thus, in this design optimization procedure, the microstrip widths and lengths $\{\vec{W}, \vec{\ell}\}$ on a selected substrate (ε_r, h, tanδ) are directly used by the HBMO algorithm (Fig. 2) and the cost function is evaluated by means of the SVRM microstrip model (Fig. 3). The 3-D SONNET–based SVRM model of the microstrip [7], [8] is employed that provides an accurate, fast and cost effective generalization from the highly nonlinear discrete mapping from the input domain M(R^4) of the microstrip width, substrate (ε_r, h) and frequency (f) to the output domain of either the characteristic impedance Z_0 or effective dielectric constant ε_{eff}.

(iii) Finally the proposed HBMO–based design is applied to the design of a typical ultra-wide-band LNA with NE3512S02 on a substrate of Rogers 4350 ($\varepsilon_r = 3.48$, $h = 1.524$ mm, tan$\delta = 0.003$) for the maximum output power and the noise figure F(f) = 1 dB within the 5-12 GHz using the T-type of microstrip matching circuits. Furthermore the completed amplifier design is also compared with the GA, PSO and the simple HBMO designs and the proposed HBMO design is resulted with its outstanding performance, besides the verification is also made using the circuit simulator AWR.

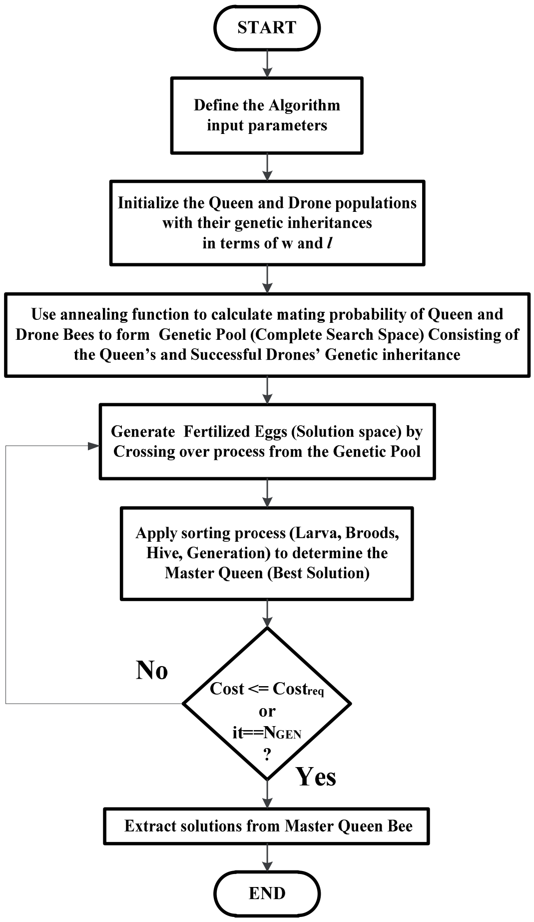

Fig. 2. Flow chart of the HBMO algorithm.

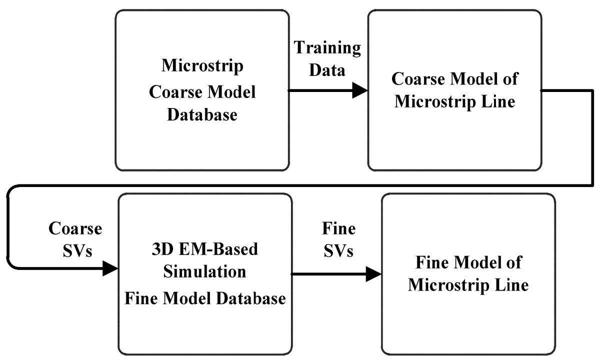

Fig. 3. The cost effective SVRM modeling of microstrip lines.

The article is organized as follows: Sections 2 and 3 give the objective and variables of the design optimization of the matching circuits. The HBMO with the royal jelly feed algorithm takes place in Section 4. As a test vehicle of the presented methodology, design of typical wideband low-noise amplifiers using T-type of microstrip matching circuits is discussed comparatively with the GA, PSO and the simple HBMO designs in Section 5 with together their validated performances. Finally the paper ends with conclusions in Section 6.

2. Design Objectives

2.1 Objective for Determination of FDT

In this design optimization problem, the design objective is the maximum output power delivery and the required noise. For this purpose, firstly the gain G_T is maximized with respect to the Z_S under the matched output port provided that required noise F is satisfied, which can be expressed as: load Z_L impedances of the active device at a chosen bias condition (V_{DS}, I_{DS}) of the device as follows:

$$G_T = \frac{P_L}{P_{avs}} = G_{AV}(Z_S)\,M_{out}(Z_S, Z_L) \tag{4}$$

where

$$G_{AV}(Z_S) = \frac{|z_{21}|^2}{|z_{11}+Z_S|^2}\frac{r_S}{r_{out}}$$

$$M_{out}(Z_S, Z_L) = 1 - \left|\frac{Z_{out}-Z_L^*}{Z_{out}+Z_L}\right|^2 \le 1 \tag{5}$$

$$Z_{out} = z_{22} - \frac{z_{12}z_{21}}{z_{11}+Z_S}$$

$$F(Z_S) = \frac{(S/N)_i}{(S/N)_o} = F_{min} + \frac{R_n|Z_S - Z_{opt}|^2}{|Z_{opt}|^2 r_S} \tag{6}$$

Here z_{ij}, $i, j = 1, 2$ and R_n, F_{min} and $Z_{opt} = r_{opt} + jx_{opt}$ are respectively, the z-parameters obtained by conversion of the [S]- parameters and noise [N]- parameters at an operation condition $\{(V_{DS}, I_{DS}), f\}$.

Thus, hereafter the problem of determination of the source impedance $Z_S = r_S + jx_S$ of a microwave transistor can be described as a mathematically constrained optimization problem so that the gain $G_{AV}(r_S, x_S)$ given by (5) will be maximized and simultaneously the required noise figure will be met using the $F(r_S,x_S)$ equation (6) at each sample frequency throughout the required operation bandwidth. Thereby the multi-objective cost function of this constrained optimization process can be expressed as:

$$Cost = e^{-\psi_1 G_{AV}(r_S, x_S, f_i)} + \psi_2\left|F(r_S, x_S, f_i) - F_{req}(f_i)\right| \tag{7}$$

with the following constraints

$$\Re e\{Z_S\} > 0,\ \Re e\{Z_L\} > 0 \ . \tag{8}$$

$$\Re e\{Z_{in}\} = \Re e\{z_{11} - \frac{z_{12}\ z_{21}}{z_{22}+Z_L}\} > 0$$

$$\Re e\{Z_{out}\} = \Re e\{z_{22} - \frac{z_{12}z_{21}}{z_{11}+Z_S}\} > 0 \tag{9}$$

$$F_{req} \ge F_{min} \ . \tag{10}$$

In (7), $\Psi_1$and Ψ_2 are the weighting coefficients which can be chosen during the optimization process by trial, which in our case are taken as unity. Thus, the smaller cost is the fitter optimization process we have.

2.2 Design Objective of the Matching Networks

Thus, we have the transistor terminations given by (1) and (2). In the design optimization procedure, the gain of the input/output matching two-port terminated by the complex conjugate of the obtained in the previous subsection, is maximized over the required bandwidth:

$$cost\,(\vec{\vartheta}) = Minimum \sum_i (1 - G_{T_i}(f_i, \vec{\vartheta})) \tag{11}$$

where $\vec{\vartheta}$ is the design variable vector which consists of the microstrip widths and lengths of the problem matching circuit and G_{Ti} is the power gain of the same matching circuit at the sample frequency f_i. In the worked example T-type matching circuits are considered to be designed. The proposed method can be applied without any difficulty to another different type of matching circuit such as π- or L-types or any other kind of matching circuits. In that case, the gain function $G_{T_i}(f_i, \vec{\vartheta})$ given in (11) should be evaluated for the considered matching circuit.

3. Design Variables: Microstrip Widths and Lengths $\{\vec{W}, \vec{\ell}\}$

Design variables are the microstrip widths, lengths $\{\vec{W}, \vec{\ell}\}$ of the input/output matching networks on a selected substrate $\{\varepsilon_r, h, \tan\delta\}$, which are mapped in the continuous manner to the characteristic impedance Z_0 and the dielectric constant ε_{eff} of the equivalent transmission line to be used in the design optimization process via the two 3-D SONNET-based SVRMs [7], [8]. Here, the input domain of the microstrip SVRM model is four-dimensioned $M(R^4)$ within $\{0.1\text{ mm} \le W \le 4.6\text{ mm},\ 2 \le \varepsilon_r \le 10,\ 0.1\text{ mm} \le h \le 2.2\text{ mm},\ 2\text{ GHz} \le f \le 14\text{ GHz}\}$ and the output domains of the Z_0 and ε_{eff} correspond to $\{3\ \Omega \le Z_0 \le 240\ \Omega\}$ and $\{1.5 \le \varepsilon_{eff} \le 9.7\}$, respectively. The mathematical bases of Support Vector Regression can be found in [7] in details.

3.1 Building Knowledge-Based Microstrip SVRM Model

Knowledge-based Microstrip SVRM is given as block diagram in Fig. 3 where the quasi-TEM microstrip analysis formulae [10] is used as a coarse SVRM model data base by means of which $n_{freq} \times n_{\varepsilon} \times n_{\mathrm{h}} \times n_{\mathrm{w}} = 5 \times 5 \times 4 \times 10 = 1000$ number of $(\vec{x}_i, \vec{y}_i)$ data pairs are obtained to train the coarse SVRM, where n_{freq}, n_{ε}, n_h, n_w are the number of the samples for the frequency, the dielectric constant, the substrate height and width, respectively. Tab. 1 gives the accuracy of the "Z_0" coarse model with the number of the SVs and the radius of selection tube ϵ. 402 and 367 fine SVs obtained from 3-D SONNET simulator are used to train the fine "Z_0" and "$\varepsilon_{\mathrm{eff}}$" SVRMs, respectively with the accuracy at least 99.4 % (Fig. 4b). Thus the substantial reduction (up to 60 %) is obtained utilizing sparseness of the standard SVRM in number of the expensive fine discrete training data with the negligible loss in the predictive accuracy and the resulted fine microstrip SVRM model can be considered as accurate as the 3-D EM simulator [9] and as fast as the analytical formulae [10]. The typical comparative prediction curves of the microstrip SVRM model take place in Figs. 4a and 4b which give variations of the characteristic impedance Z_0 and the effective dielectric constant $\varepsilon_{\mathrm{eff}}$ with microstrip width W resulted from the fine SVRM model for various dielectrics with $h = 1.28$ mm at 4 GHz, respectively.

Epsilon (ϵ)	Number of SVs	Accuracy (%)
0.05	583	99.4
0.07	402	98.6
0.1	279	97.9

Tab. 1. Accuracy of the coarse SVRM model.

In the next section, "HBMO with Royal Jelly" algorithm will be given to determine the matching microstrip widths, lengths $\{\vec{W}, \vec{\ell}\}$ on a chosen substrate $\{\varepsilon_r, h, \tan\delta\}$ to satisfy the required noise and the maximum power delivery over the required bandwidth of a selected transistor.

The FDT is determined using the simple HBMO version without the Royal Jelly.

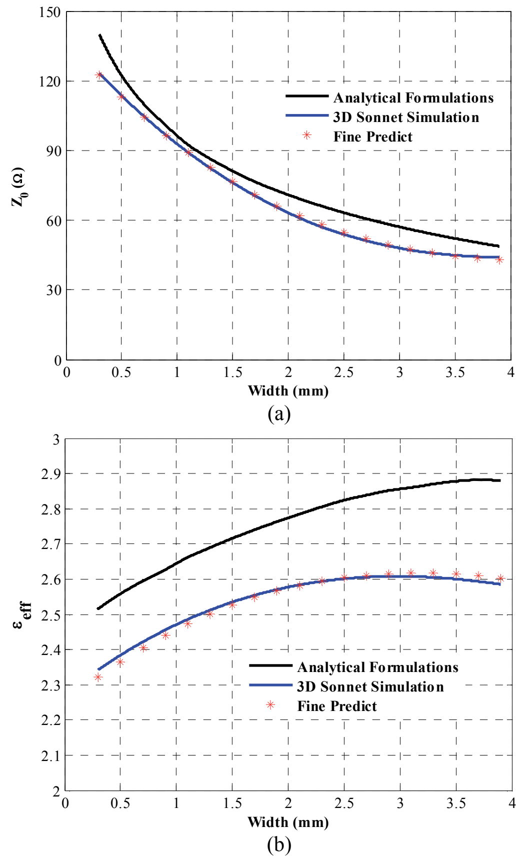

Fig. 4. Comparative variations of (a) Characteristic impedance Z_0, (b) Effective dielectric constant $\varepsilon_{\mathrm{eff}}$ vs width of the analytical formulations, Fine Model and the 3-D SONNET simulation on the substrate $\varepsilon_r = 3.48$, $h = 1.524$ mm at $f = 8$ GHz.

4. HBMO with Royal Jelly for the Amplifier's Matching Network Design Problem

4.1 Working Stages of the Proposed HBMO

The HBMO with Royal Jelly for the design of the T-type microstrip front-end amplifier problem can be described in the following stages (Fig. 2):

Stage 1: Definition of input data

In this stage, the number of the Drone bees (N_{Drone}), maximum iteration number ($t_{\max}$), sizes of the genetic inheritance of the Master Queen Q_{M} and each Drone bee D_j, (m_{Q}, m_{D}); maximum number of feeding times of the Master Queen Q_{M} with Royal Jelly (N_{RJ}), Maximum ($E_{\max}$) and minimum ($E_{\min}$) energies of the Queen at the start and end of the mating flights, respectively, and the required cost $cost_{\mathrm{req}}$ are defined by the user. In the algorithm, the numbers of the Hive (N_{Hive}), Brood (N_{Brood}), Larva (N_{Larva}), Fertilization ($N_{\mathrm{fertilization}}$) are set equal to ($N_{\mathrm{Gen}}$)which is taken to be equal to $t_{\max}$ and the total egg number $N_{\mathrm{Egg}} = (N_{\mathrm{Gen}})^5$.

Stage 2: Define Queen Q and Drone's D populations with their genetic inheritances

$$Q\_population = [Q_1, Q_2, \ldots\ldots, Q_{N_{\mathrm{Hive}}}]^{\mathrm{t}}$$
$$D\_population = [D_1, D_2, \ldots\ldots, D_{N_{\mathrm{Drone}}}]^{t} \tag{12}$$

where Q_i and D_j members of the Queen and Drone population are defined based on the optimization variables, respectively as below:

$$Q_i = \begin{bmatrix} w_{1Qi}, w_{2Qi}, w_{3Qi} \\ \ell_{1Qi}, \ell_{2Qi}, \ell_{3Qi} \end{bmatrix}_{2x3}$$
$$D_j = \begin{bmatrix} w_{1Dj}, w_{2Dj}, w_{3Dj} \\ \ell_{1Dj}, \ell_{2Dj}, \ell_{3Dj} \end{bmatrix}_{2x3} \tag{13}$$

Furthermore genetic inheritance belonging to each Queen Q_i and Drone D_j are also defined in terms of the optimization variables as follows:

$$Q_{iGen} = \begin{bmatrix} W_1, W_2, W_3 \\ L_1, L_2, L_3 \end{bmatrix}_{2x3} \quad D_{jGen} = \begin{bmatrix} W_1, W_2, W_3 \\ L_1, L_2, L_3 \end{bmatrix}_{2x3} \tag{14}$$

$W_i = [w_i]_{\text{mx }1}$, $L_i = [\ell_i]_{\text{mx }1}$, $i = 1,2,3$ and $m_Q = 1000$ for Queens and $m_D = 100$ for each Drone bee as the user-defined parameters.

The genetic inheritance of a Queen bee $Q_{i\text{Gen}}$ in (14) is completely passed to the next generation while only $D_{j\text{Gen}}$ belonging to the N_{Drs} drones which had successful mating flights passed down to the next generation by being collected into the Queen Bee's spermatheca. In the next stage, initialization of the Queen and Drones population and generation of the Genetic inheritances will be given.

Stage 3: Initialize the Queen and Drones population and their genetic inheritances

Initialize all the elements of the Q_population to zero excluding the first one: $Q_i = 0$, $i \neq 1$, the first Queen will be called hereafter as the Master Queen Q_M that will give birth to the members of all the hives. The Master Queen Q_M, the D_Population and their genetic inheritances defined in (12-14) are randomly initialized as follows:

$$w = [C_1 - C_2]\,\text{rand}(.) + C_2\text{rand}(.) \quad , \tag{15}$$

$$\ell = [C_3 - C_4]\,\text{rand}(.) + C_4\text{rand}(.) \quad . \tag{16}$$

where C_i, $i = 1, 3$ and $i = 2, 4$ are the given upper and lower boundaries for the widths and lengths of the microstrip lines, respectively. Rand (.) is a random generator which generates random values ε (0, 1). Then calculate Fitness Values of Master Queen Q_M and the D_ Population in (12) using either (7) or (8-11). In the next stage, spermatheca of the Master Queen Q_M will be generated.

Stage 4: Generate the Master Queen's spermatheca (Mating Flights)

At the start of the mating, Master Queen Q_M flies with her maximum energy $E_{\max}$. A drone is randomly selected from the drone population in (12) and mates with the Master Queen Q_M probabilistically using an annealing function as follows:

$$\text{Prob}(Q_M, D) = e^{\left(-\frac{|\Delta f|}{E(t)}\right)} \tag{17}$$

where $\Delta f = \left| f_{Q_M} - f_{Dj} \right|$, f_{Q_M} is Fitness of the Master Queen Q_M, f_{Dj} is Fitness of the j^{th} Drone, D_j and the finesses are evaluated using the cost function defined by (7) and (13).

The calculated Prob(Q_M, D) of the mating flight is compared with a random value ∊ (0, 1) and if it is greater than the random value, the mating will be assumed to be successful attempt and the corresponding Drone's sperms (Drone's genetic inheritances) will be added to the spermatheca:

$$\text{Prob}(Q_M, D) \geq \text{Rand}(.) \ . \tag{18}$$

After each mating Master Queen's energy level is decreased with the random decaying coefficient:

$$\alpha(t) \in (0, 1)\ , \ E(t+1) = E(t) \times \alpha(t)\ . \tag{19}$$

If the current energy level of the Master Queen Bee Q_M is lower than the minimum level, the mating flights will be stopped, thus the Master Queen Q_M can fly back to the Hive to give births to new members of the colony as given in the stages (5-6), otherwise the mating flights will be continued until there are no more drones in the D population to be mated.

Stage 5: Generate the Genetic Pool (GP)

If a mating flight is successful, the Master Queen Bee Q_M will accept all the sperms of the partner drone into her spermatheca to generate the genetic pool with her genetic inheritance, from where new generation of the entire colony will have their genetic identities. Size of the genetic pool will be increased with the number of the successfully performed mating flights, and the Master Queen Q_M 's genetic inheritance completely passes to next generation while solely the $D_{j\text{Gen}}$ s belonging to the N_{Drs} drones having successful mating flights till the end of her mating flight, thus the genetic pool can be defined as

$$GP = \begin{bmatrix} W_{1GP}, W_{2GP}, W_{3GP} \\ L_{1GP}, L_{1GP}, L_{1GP}, \end{bmatrix}_{2x3} \tag{20}$$
$$W_{iGP} = \left[w_i \right]_{mx1} \ L_{iGP} = \left[\ell_i \right]_{mx1} \ i = 1,2,3$$

Here $m = 1000 + 100N_{\text{Drs}}$ and $N_{\text{Drs}} \leq N_{\text{Drone}}$ is the number of the drones each of which had a successful mating flight with the Master Queen Bee Q_M. Thus, in this stage we have a search space having a huge capacity with $(m)^6 = (1000 + 100N_{\text{Drs}})^6$ number of different random solutions for the T-matching circuit that means at least 10^{18} solutions with $N_{\text{Drs}} = 0$. In the following stage, generation of Egg population (Solution Space) from this genetic pool (Search Space) will be given by the crossing over process.

Stage 6: Generate the Egg population

In the proposed HBMO algorithm, gender of all new born members of the colony will be assumed as female, thus each solution can be considered as a potential Master Queen Bee candidate. The Egg_ population is defined as:

$$Egg\ population = [\text{Egg}_1, \text{Egg}_2, .., \text{Egg}_{N_{\text{Egg}}}]^t$$
$$Egg_i = \begin{bmatrix} w_{1Egg_i}, w_{2Egg_i}, w_{3Egg_i} \\ \ell_{1Egg_i}, \ell_{2Egg_i}, \ell_{3Egg_i} \end{bmatrix}_{2x3} \tag{21}$$

$i = 1,...,N_{egg}$, which is generated by crossing over among the corresponding elements of the genetic pool:

$$\begin{aligned} w_{jEgg_i} &= W_{jGP}(\mathrm{K_n},1) \\ \ell_{\mathrm{jEgg_i}} &= L_{j\mathrm{GP}}(\mathrm{K'_n},1) \end{aligned} \tag{22}$$

$\mathrm{K_n}$ and $\mathrm{K'_n}$ are randomly generated integers $\in (1, 1000 + 100N_{\mathrm{Drs}})$.Thus a sub-search space is generated as a solution space by this Egg population within the complete search space defined by the genetic pool with the $N_{\mathrm{egg}} = (N_{\mathrm{gen}})^5 = (t_{\max})^5$ couples which will be sorted rapidly for the best solution in the next stage.

Stage 7: Accelerated exploration for the new Master Queen Bee

During this phase, all the new born members of the Egg Population will be passing from the five steps to explore rapidly the search space for the selection of the new Master Queen $\mathrm{Q_M}$ (The Best solution). These five steps can be given with their sizes as follows:

1-Fertilization ($N_{\mathrm{fertilization}}$), 2-Larva ($N_{\mathrm{Larva}}$), 3-*B*rood ($\mathrm{N_{brood}}$), 4-Hive ($N_{\mathrm{Hive}}$), and 5-Generation ($N_{\mathrm{Gen}}$), size of each of these steps is equal to maximum iteration number which is taken to be equal to 20 in our application. The accelerated exploration is based on the “sorting” step by step and can briefly be summarized as follows: In each step, the current entire population is divided into the sub-populations having (N_{Gen}) members, then the best member with the minimum cost value of each sub-population is promoted to the next step, and the rest members are discarded.

For $N_{\mathrm{Drs}} = 5$, we have $m = 1000 + 100\mathrm{x}5$ and 1500 elements for each of $W_{j\mathrm{GP}}$ and $L_{j\mathrm{GP}}$ vector of the genetic pool as given in (20), thus the complete search space consists of $1500^6 = 11.4 \times 10^{18}$ (W_j, ℓ_j) couples, among which $N_{\mathrm{Egg}} = 20^5 = 3.200.000$ (W_j, ℓ_j) pairs are passed to the Egg population by crossing over to generate the solution space. Sorting these 20^5 sub-groups, total 20^4 eggs (the solutions having the minimum cost values belonging to the sub-groups) are fertilized and promoted to the “Larva” stage. Then repeating the same process in the “Larva” stage, 20^3 larvas will be promoted to the “Brood” stage. So on, at the end of the competition among the queens of the $20^2 = 400$ Hives, only 20 best solutions will be passed to the “Generation” stage as the Master Queen Candidates. Since iteration is equal to “Generation” number, Master Queen Candidate of each Generation/Iteration will be compared with the current Master Queen Bee. In this final step, only (W_j, ℓ_j) couples having the minimum cost of the competition will be chosen as the new Master Queen Bee which will take new mating flights to give born to new members of the next generation of the colony. These steps can be considered as the accelerated selection of the fittest member of the entire colony. The algorithm terminates if it reaches either the maximum iteration/generation number or the required cost.

Stage 8: Feeding of the Master Queen Bee with Royal Jelly

Royal Jelly Feed aims at increasing the accuracy of the solution by minimizing the cost obtained from the global search. Therefore each element of the Master Queen Bee $\mathrm{Q_M}$ is either increased or decreased by the incremental steps N_{RJ} while the other elements remain the same, depending on the cost variation. Thus, the accuracy of the solution is increased by minimizing the cost value which is the final solution in the form of:

$$Q_M = \begin{bmatrix} w_{1Q_M}, w_{2Q_M}, w_{3Q_M} \\ \ell_{1Q_M}, \ \ell_{2Q_M}, \ \ell_{3Q_M} \end{bmatrix}_{2x3} \tag{23}$$

4.2 Characteristics the Proposed HBMO

In this work, the proposed HBMO algorithm is used effectively and efficiently to design a front-end amplifier. The features of the HBMO version can briefly be summarized as follows: Our HBMO algorithm works effectively with a single Queen called as the Master Queen and generated randomly between predefined upper and lower limitations together with her versatile genetic inheritance and has the duty of give birth to the members of the N_{hive} hives of the colony instead of one hive. The rest of Queen Population is used for registration of the Queens of the N_{hive} hives from where the Master Queen $\mathrm{Q_M}$ will be selected. Division of the entire colony into the N_{hive} hives facilitates “Sorting” process applied to the sub-colonies step by step, in the other words the search for the new Candidates is performed in a reduced number of sub-matrices instead of making a search for a single gigantic matrix. This gains the algorithm both simplicity and efficiency. The mating process is also simplified to only energy-based probabilistic decision rule to enable the more fittest solutions, and furthermore “Egg population” is defined as a random selection process based on a crossing over to generate search space as a sub-space of the entire huge solution space, besides “Royal Jelly” feed is used in algorithm to make a local search in order to improve the fitness of the Master Queen bee at the end of the each generation or iteration. Thus the comparison with the counterpart population-based algorithms verified that a robust and fast convergent algorithm with the minimal problem information is resulted for the design of a front-end amplifier.

5. Worked Example

The user-defined parameters of the HBMO algorithms are set to the following values in the design of the front-end amplifier: $N_{\mathrm{Drone}} = 20$, $t_{\max} = N_{\mathrm{Gen}} = 20$, $m_{\mathrm{Q}} = 1000$, $m_{\mathrm{D}} = 100$, $N_{\mathrm{Rj}} = 1000$, $E_{\max} = 1$, $E_{\min} = 0.2$, $cost_{\mathrm{req}} = 0.02$.

In the work example, NE3512S02 is selected as the microwave transistor and its minimum noise figure $F_{\min}(f)$ profiles are given in Fig. 5 at several bias conditions.

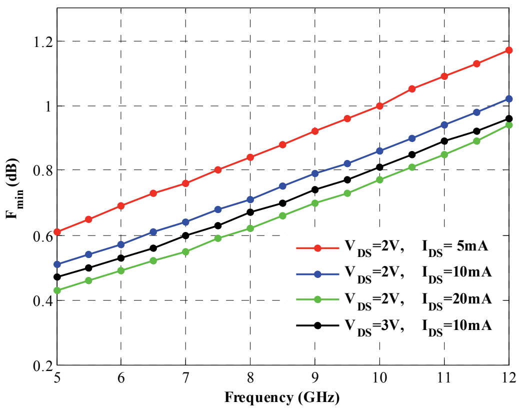

Fig. 5. Noise Figure Profiles at several bias conditions.

Furthermore, the maximum gain $G_{Tmax}(f)$ variations constrained by the minimum noise figures $F_{min}(f)$ and $F = 1$ dB are evaluated numerically using the HBMO and compared the analytical counterparts [1], [2] which are taken place in Figs. 6 and 7 at several bias conditions, respectively.

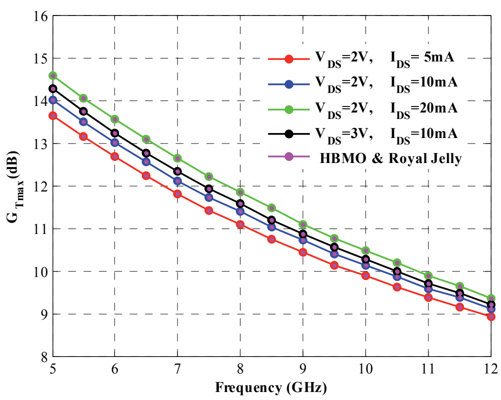

Fig. 6. Constrained Maximum gain $G_{Tmax}(f)$ by $F_{min}(f)$.

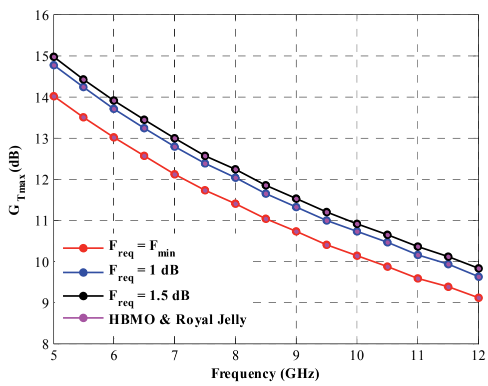

Fig. 7. Constrained Maximum Gain by $F_{req} \geq F_{min}$ frequency characteristics at the bias condition ($V_{DS} = 2$ V, $I_{DS} = 10$ mA).

The gain performance G_{Tmax} (f) constrained by F = 1 dB at the bias condition (2 V, 10 mA) is designed on the substrate of Rogers 4350 ($\varepsilon_r = 3.48$, $h = 1.524$ mm, $\tan\delta = 0.003$, $t = 0.001$ mm) along the bandwidth of 5-12 GHz. The solution spaces of the T-type matching circuits in Fig. 8 are shown in Tab. 2.

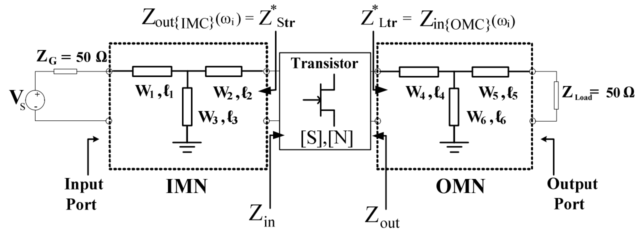

Fig. 8. LNA with T- type Microstrip Matching Networks.

W_1 (mm)	W_2 (mm)	W_3 (mm)	W_4 (mm)	W_5 (mm)	W_6 (mm)
4.58	4.99	4.32	1.28	3.79	4.13
ℓ_1 (mm)	ℓ_2 (mm)	ℓ_3 (mm)	ℓ_4 (mm)	ℓ_5 (mm)	ℓ_6 (mm)
13.93	5.37	0.77	1.73	5.65	14.36

Tab. 2. Solutions of the T type input and output microstrip matching elements for the maximum output power and the noise figure $F(f) = 1$ dB.

Impedance mismatching at the input and output ports are given as compared with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and HBMO with and without Royal Jelly in Figs. 9 and 10, respectively.

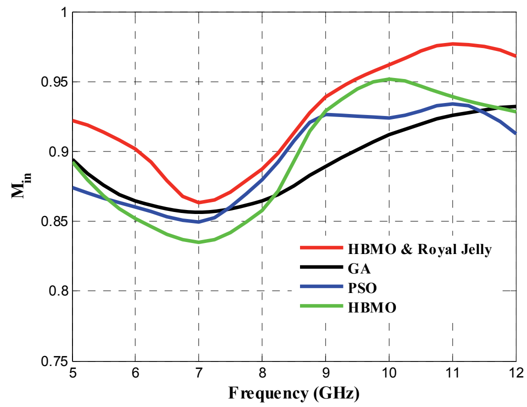

Fig. 9. Comparison of algorithm for impedance mismatching at the input port.

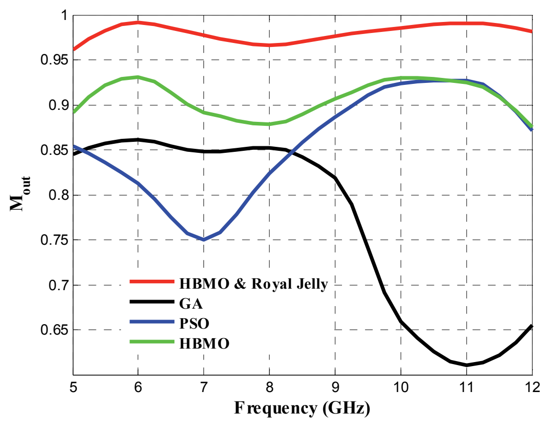

Fig. 10. Comparison of algorithm for impedance mismatching at the output port.

The resulted gain, noise performances, input and output reflections of the amplifier designed by HBMO with Royal Jelly are given in Figs. 11, 12, 13, 14, respectively as compared with the targeted performances and obtained by the AWR circuit and 3-D EM simulators.

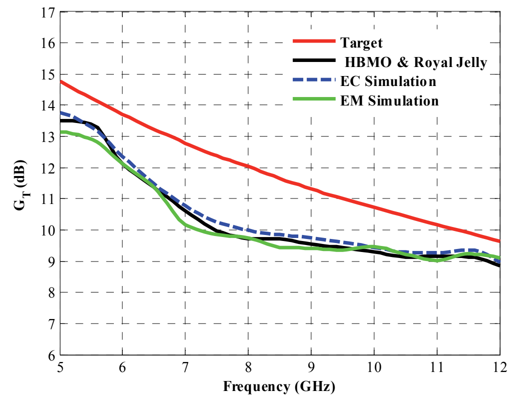

Fig. 11. Comparative gain performance of the amplifier for the maximum power delivery and the noise figure of $F(f)$ = 1 dB.

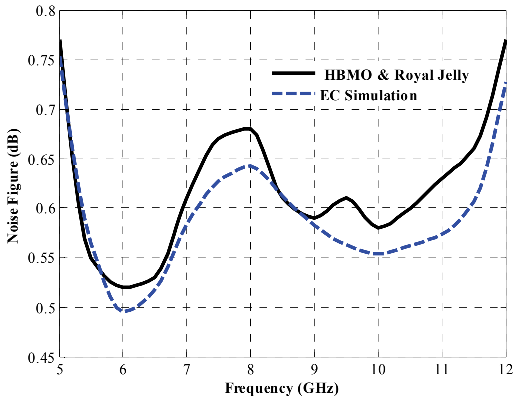

Fig. 12. Synthesized noise performance of the T-type amplifier.

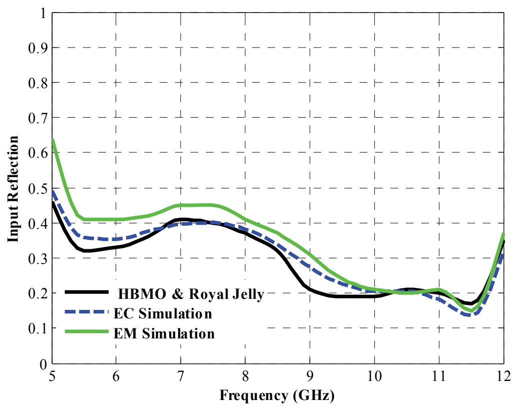

Fig. 13. Input reflection of the T-type amplifier.

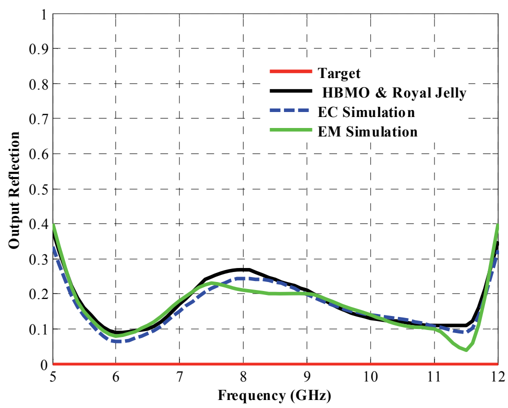

Fig. 14. Output reflection of the T-type amplifier.

Furthermore the cost and execution time with iteration number of the used counterpart's algorithms which are GA, PSO, and HBMO with and without Royal Jelly are given in Fig. 15.

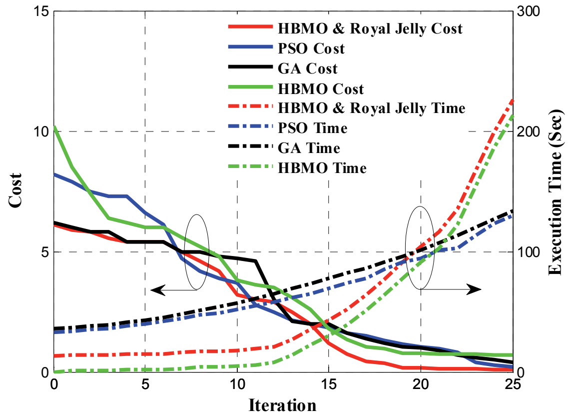

Fig. 15. Cost and execution time variations for PSO, GA and HBMO & Royal Jelly.

The optimization parameters of the studied algorithms are given in Tab. 5, the parameters of the PSO and GA are taken as their default values of the MATLAB Optimization tool, MATLAB 2010b [20]. The cost values and execution times at the 20th iteration of a random run are given in Tab. 3 performed by the Intel Core i7 CPU, 1.60 GHz Processor, 6 GB RAM. Furthermore the statistical analysis is performed benchmarking of the selected algorithms for 10 times of tries depicted in Tab. 4 that result in a high success rate of the proposed algorithm. Thus one can infer the effectiveness and efficiency of the proposed HBMO based design by comparing it with the GA, PSO and the simple HBMO based designs.

Algorithm	**Cost**	**Execution Time (Sec)**
HBMO &Royal Jelly	0.17	84
HBMO	0.77	71
PSO	1.15	84
GA	1.05	89

Tab. 3. Benchmarking at 20th iteration.

Algorithm	**Worst**	**Best**	**Mean**
HBMO &Royal Jelly	0.29	0.12	0.18
HBMO	0.9	0.65	0.74
GA	1.27	0.95	0.99
PSO	1.15	0.9	0.96

Tab. 4. Benchmarking of cost variation for 10 tries at 20th iteration for all algorithms.

Algorithm	**Population**	**Maximum Iteration**	**Special Parameters**
HBMO& Royal Jelly	Iteration^5	25	N_{Drone}= 20, E_{max} = 1, E_{min} = 0.2, N_{RJ} Step Size = ±0.01
HBMO	Iteration^5	25	N_{Drone}=20, E_{max} = 1, E_{min} = 0.2
GA	30	25	Gaussian Mutation
PSO	30	25	Learning factors $c_1 = c_2 = 2$

Tab. 5. User defines parameters of the algorithms.

6. Conclusions

This work has gathered the analytical and novel artificial intelligence techniques developed by our research team [11-19], to design a front-end amplifier that is formulated as an optimization problem each ingredient of which is carried out rigorously on the mathematical basis. In fact, this front-end amplifier design is based on a constrained optimization problem with the different objectives which are the maximum signal power delivery and the required noise. Besides in this work, the cost effective 3-D SONNET-based SVRM microstrip model is used as a fast and accurate model worked out by our research group in the design process of the microstrip matching networks. Another originality is building of a simple and efficient version of the HBMO to be used in the front-end amplifier design. The HBMO combines the powers of simulated annealing, genetic algorithms to search for the best possible solution to the problem under investigation within a reasonable computing time. Furthermore, a simple local heuristic is combined with the HBMO to increase the accuracy without decreasing much the computational efficiency. Thus, the significance of the work for the microwave circuit theory can mainly be itemized as follows:

(i) First of all, the design needs solely the fundamental microwave circuit knowledge; (ii) Design target is based on the potential performance of the used active device that is obtained by solving numerically the nonlinear gain, noise and input and output mismatching equation using the HBMO subject to the design objective; (iii) In the design of the input and output microstrip matching circuits, the cost effective microstrip SVRM model is used as a fast and accurate model so that it facilitates to obtain directly all the matching microstrip widths, lengths $\{\vec{W}, \vec{\ell}\}$ on a chosen substrate to satisfy the maximum power delivery and the required noise over the required bandwidth of a selected transistor; (iv) Microstrip matching circuit in any configuration can be easily synthesized by the HBMO with the royal jelly fast and accurately compared to the other counterpart evolutionary algorithms.

It can be concluded that the paper presents an attractive design method for a front-end amplifier design based on the transistor potential performance, and it can be adapted to design of the other types of linear amplifiers.

References

[1] DEMIREL, S. A generalized procedure for design of microwave amplifiers and its applications. *PhD Thesis* (in Turkish). Yıldız Technical University, Istanbul, Turkey, 2009.

[2] DEMIREL, S., GÜNEŞ, F. Performance characterization of a microwave transistor for maximum output power and the required noise. *IET Circuits Devices Syst*, 2013, vol. 7, no. 1, p. 9–20.

[3] HADDAD, O. B., AFSHAR, A., MARINO, M. A. Honey-Bees Mating Optimization (HBMO) algorithm: A new heuristic approach for water resources optimization. *Water Resources Management*, 2006, vol. 20, p. 661–680.

[4] AFSHAR, A., HADDAD, O. B., MARINO, M. A., ADAMS, B. J. Honey-Bee Mating Optimization (HBMO) algorithm for optimal reservoir operation. *Journal of the Franklin Institute*, 2007, vol. 344, p. 452–462.

[5] FATHIAN, M., AMIRI, B., MAROOSI, A. Application of Honey-Bee Mating Optimization algorithm on clustering. *Applied Mathematics and Computation*, 2007, vol. 190, p.1502–13.

[6] NIKNAM, T. Application of Honey Bee Mating Optimization on distribution state estimation including distributed generators. *J. Zhejiang University SCIENCE A*, 2008, vol. 9, p.1753–1764.

[7] VAPNIK, V. *The Nature of Statistical Learning Theory*. New York: Springer – Verlag, 1995.

[8] KESKIN, A. K. Design optimization of ultra wide band microstrip amplifier using 3-D Sonnet-based SVRM with particle swarm intelligence. *MSc Thesis*. Yıldız Technical University, Istanbul, Turkey, 2012.

[9] http://www.sonnetsoftware.com/products/sonnet-suites/

[10] POZAR, D. M. *Microwave Engineering*. John Wiley & Sons, 2012.

[11] GÜNEŞ, F., GÜNEŞ, M., FIDAN, M. M. Performance characterization of a microwave transistor. *IEE Proceedings-Circuits, Devices and Systems*, 1994, vol. 141, no. 5, p. 337–344.

[12] GÜNEŞ, F., ÇETINER, B. A. A Novel Smith chart formulation of performance characterization for a microwave transistor. *IEE Proceedings -Circuits Devices and Systems*, 1998, vol. 145, no. 6, p. 419–428.

[13] GÜNEŞ, F., ÖZKAYA, U., DEMIREL, S. Particle swarm intelligence applied to determination of the feasible design target for a low–noise amplifier. *Microwave and Optical Technology Letters*, 2009, vol. 51, p. 1214–1218.

[14] MAHOUTI, P., GÜNEŞ, F., DEMIREL, S. Honey–Bees Mating Algorithm applied to feasible design target space for a wide–band front–end amplifier. In *ICUWB 2012- IEEE International Conference on Ultra-Wideband*. Syracuse (NY), 2012, p. 251 – 255, DOI: 10.1109/ICUWB.2012.6340411.

[15] GÜNEŞ, F., TÜRKER, N., GÜRGEN, F. Signal-noise support vector model of a microwave transistor. *Int J RF and Microwave CAE,* 2007, vol. 17, no. 4, p. 404–415.

[16] GÜNEŞ, F., TORPI, H., GÜRGEN, F. A multidimensional signal-noise neural network model for microwave transistors. *IEE Proceedings-Circuits Devices and Systems*, 1998, vol. 145, no. 2, p. 111–117.

[17] DEMIREL, S., GÜNEŞ, F., TORPI, H. Particle swarm intelligence use in feasible design target space of a microwave transistor for a wide-band output-stage requirements. In *ICUWB- 2012 IEEE International Conference on Ultra-Wideband.* Syracuse (NY), 2012, p. 246-250, DOI: 10.1109/ICUWB.2012. 6340403.

[18] GÜNEŞ, F., KESKIN, A. K., DEMIREL, S. Genetic Algorithm applied to microstrip implementation of matching circuits for a UWB low-noise amplifier. In *IEEE International Conference on Ultra-Wideband*. Syracuse (NY), 2012, p. 241 – 245, DOI: 10.1109/ICUWB.2012.6340406.

[19] GÜNEŞ, F., TOKAN, N. T., GÜRGEN, F. A knowledge-based support vector synthesis of the transmission lines for use in microwave integrated circuits. *Expert Systems with Applications*, 2010, vol. 37, no. 2, p. 3302–3309.

[20] MATLAB and Neural Networks Toolbox Release 2012b, the MathWorks, Inc., Natick, Massachusetts, United States.

About Authors...

Filiz GUNES received her M.Sc. degree in Electronics and Communication Engineering from the Istanbul Technical University. She attained her Ph.D. degree in Communication Engineering from the Bradford University in 1979. She is currently a full professor in Yıldız Technical University. Her current research interests are in the areas of multivariable network theory, device modeling, computer aided microwave circuit design, monolithic microwave integrated circuits, and antenna arrays.

Salih DEMIREL has received M.Sc. and Ph.D. degrees in Electronics and Communication Engineering from Yıldız Technical University, Istanbul, Turkey in 2006 and 2009, respectively. He has been currently working as an assistant professor in the same department. His current research interests are among of microwave circuits especially optimization of microwave circuits, broadband matching circuits, device modeling, computer-aided circuit design, microwave amplifiers.

Peyman MAHOUTI received his M.Sc. degree in Electronics and Communication Engineering from the Yıldız Technical University in 2012. He has been currently in Ph.D. program of Yıldız Technical University. The main research areas are optimization of microwave circuits, broadband matching circuits, device modeling, computer-aided circuit design, microwave amplifiers.