THE ANNALS OF "DUNAREA DE JOS" UNIVERSITY OF GALATI
FASCICLE III, 2002 ISSN 1221-454X
ELECTROTECHNICS, ELECTRONICS, AUTOMATIC CONTROL, INFORMATICS

A DIFERENT APPROACH IN THE PARAMETERS' IDENTIFICATION OF A JFET USING GENETIC ALGORITHMS

Radu BELEA, Liviu BELDIMAN

Department of Control System and Industrial Informatics, University "Dunărea de Jos" of Galati, Faculty of Electrical Engineering and Computer Science, Domneasca Street 47, 6200, Galați, RomaniaPhone: (+40) 236-414872, Phone+Fax: (+40) 236-460182, E-Mail: Radu.Belea@ugal.ro., Liviu.Beldiman@ugal.ro.

Abstract: The genetic algorithms are developing in three directions: the genetic algorithms theory, the genetic algorithms programming and the study of the problems that can be solved with genetic algorithms. In this paper it is presented a study on the identification of the parameters of a JFET (Junction Field Effect Transistor). The problem is very exciting because the JFET has two mathematical models: an empirical one, and an analytic one, both of the models being nonlinear in parameters. In a parametric identification problem, it is minimized the distance between an experimental data set and an analytical function, which represent the mathematical model of the studied phenomenon. Basically, a genetic algorithm can maximize a fitness function, which is a positive defined function whose maximum is searched. However, genetic algorithms can also solve minimum problems, on condition that to the minimum problem can be applied an algebraic transform or a rank based transform in a maximum problem.

Keywords: genetic algorithm, parametric identification, objective function, fitness-like function, Junction Field Effect Transistor.

1. INTRODUCTION

A physical process is a physical object that has at least one measurable input value and one measurable output value. The identification of a physical process has two stages:

- o Finding an adequate mathematical model for the physical process.
- o Specifying the parameters' values for that mathematical model.

The term "parametric identification", although well known, is a little bit vague, because the verb "to identify" means to find, to specify, an element of a discrete set, while the "parameter" is usually a real number. In fact, the parametric identification problem is an optimization problem, which searches the best value combination for the model parameter set.

In parametric identification problems one should start from an experimental data set $\{(y_n, u_n)\}$, $n = 1 \ldots m$ and a mathematical model, $y = g(u; x)$, where y is the output, u is the input vector and x is the model parameter vector. Usually, it must be minimized a quadratic objective function of type:

$$(1)\quad f(x) = \sum_{n=1}^{m} \left(g(u_n; x) - y_n\right)^2 ,$$

where $\sqrt{f(x)}$ is the distance between data set and the mathematical model. If the mathematical model is

This paper was recommended for publication by Emil CEANGĂ

linear in parameters, then the last squares method can be used, but in many cases the physical models are nonlinear functions and in this case the optimization methods who use derivatives proves to be very difficult.

Kristinsson (1992) revives the use of genetic algorithms in parametric identification techniques of dynamic systems. Kristinsson uses the genetic algorithm known as SGA (Simple Genetic Algorithm), with genes binary coded, as it is described in Goldberg (1991) or in Michalewicz (1994). The objective function is of type minimum distance and it is transformed in a fitness-like function through a variant of the ranking selection method (transform (6), briefly presented in section 3 of this paper). In the article it is presented the parametric identification results of a discrete model and a continuous one, and the results are compared with an identification realized with the instrumental variables method. It is also presented the identification results of the parameters of a nonlinear model of a servomotor, which acts with friction.

In Maclay and Dorey (1995) it is presented a case of identification of a nonlinear model of a vehicle engine and a trailer. In the model it is considered the dynamic given by the vehicle mass, the trailer mass, the coupling elasticity constant and the action of the friction forces. Some parameters were calculated from direct measurements, but 9 parameters were determined minimizing the objective function with the help of SGA genetic algorithm. The objective function was turned into a fitness-like function with transform (2) (presented in section 2 of this paper). The results obtained with the help of the genetic algorithm were compared with the ones obtained by minimizing the objective function with the Levenberg - Marquartd method.

Bastien (1997) uses the genetic programming in order to identify the static nonlinear function that describes the functioning of a gas-fired furnace. The genetic algorithm was more complicated because it had to establish the structure of the mathematical model that was used to identify the nonlinear model. The identification was done on a data set of 220 (y_i, u_i) pairs, where the inputs u_i are gas and air flow rates and the output y_i is the CO_2 concentration from the burned gases.

This paper has the following structure: in section 2 there are presented some algebraic methods used to transform a function of minimum into a fitness-like function. In section 3 there is presented the ranking selection method in which the probability to act in reproduction according with the position in a list. In section 4 there are introduced two mathematical models used to the parametric identification of the JFET. In section 5 there are presented the genetic algorithm and the identification results. In the last section the research results are summarized.

2. THE ALGEBRAIC TRANSFORM OF A MINIMUM FUNCTION INTO A FITNESS-LIKE FUNCTION

Given a vectorial function $f_{min}(x)$, $x \in R^n$ that has to be minimized, then the transform of the function $f_{min}(x)$ into a fitness-like function $f_{max}(x)$ must carry out the following conditions:

- The function $f_{max}(x)$ must be positively defined;
- The functions $f_{min}(x)$ and $f_{max}(x)$ must have the same position for the extreme points;
- The extreme order must be switched.

The simplest way of transform the objective function $f_{min}(x)$ into a fitness-like function $f_{max}(x)$ is the transform:

$$(2)\quad f_{max}(x) = \begin{cases} C - f_{min}(x) & \text{if} \quad C - f_{min}(x) > 0 \\ 0 & \text{if} \quad C - f_{min}(x) \le 0 \end{cases}$$

Choosing the constant C is a difficult task because a too small value of the constant nullifies the function $f_{max}(x)$ over almost the whole search space, while choosing a too bigger value for the constant C leads to a flat top function.

For example the minimum of the function is searched

$$(3)\quad f_{min}(x) = 8\ (x_1 - 2/3)^2 - 8\ (x_2 - 2/3)^2$$

over the space $X_1, X_2 \in [0,1]$. For $C = 20$, with the transform (3), the fitness-like function from the figure 1 is obtained.

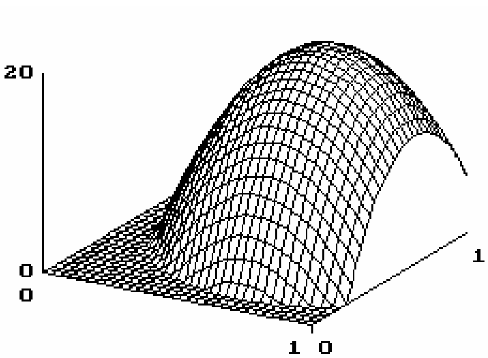

Figure 1. Modifying the function (3) into a fitness-like function with transform (2).

To overcome the disadvantages of the transform (3), the Cauchy transform can be used:

$$(4)\ \ f_{max}(x) = \frac{1}{1 + c \cdot f_{min}(x)}$$

where c is a constant chosen so that $c \cdot f_{min}(x_{min}) << 1$. If the transform (4) is applied to function (2) for $c = 1$, then it is obtained the fitness-like function from figure 2.

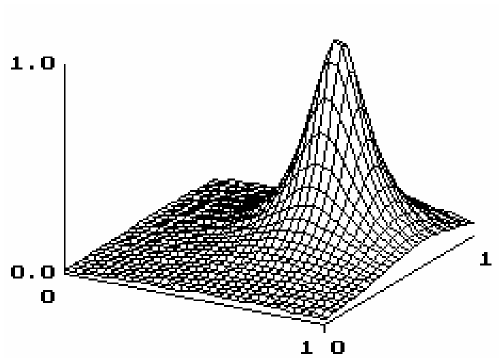

Figure 2. Modifying the function (3) into a fitness-like function by transform (4).

If the value of the function in the minimum point $f_{min}(x_{min}) \to 0$ and the constant c is correctly chosen, then the function $f_{max}(x)$ has a pronounced maxim even if the function $f_{min}(x)$ is of type minimum flat. In the case presented in figure 2, the increase of the constant c leads to the “sharpening“ of the maximum.

A typical case of positive defined, minimum objective function is the function of type “minimum distance”. If the measurements from which the objective function is calculated are error affected, than the function $f_{min}(x)$ has a minimum flat shape and its value in the minimum point $f_{min}(x_{min})$ is big. So, it is difficult to accomplish the condition $c \cdot f_{min}(x_{min}) << 1$, without having the function $f_{min}(x)$ turned into a maximum flat top function. In this case, the next transform may be used:

$$(5)\ \ f_{max}(x) = \frac{1}{1 + c \cdot \left(f_{min}(x) - C\right)}\ ,$$

where the constant c is chosen on the same criteria as in the case of the transform (4). At the first experiment the constant $C \geq 0$ is set to 0. In the next ones the constant C is adjust such that:

$$(6)\ \ 0 \leq c\left(f_{min}(x_{min}) - C\right) << 1$$

3. THE RANKING SELECTION METHOD

In a SGA genetic algorithm the proportional selection method is used and the probability of an individual to be picked out for reproduction is proportional with his fitness function value. This method reproduces the natural selection principle but it also has some disadvantages:

- If an individual has its fitness function much higher than the average (the super-individual problem), then it is possible to participate alone at the creation of the new generation. This fact will lead to the loss of the population diversity and to the premature convergence of the algorithm;

- If the differences between the fitness functions of the individuals are very small (the flat top problem), then the population cannot evolve and the genetic algorithm is reduced to a random search optimization method.

The term “ranking selection” comes from the verb “to rank” that means “to classify”. The ranking selection method avoids these disadvantages, as it calculates the selection probability in function of the position held by the individual in a rank that contains all the individuals in the population arranged antitone by the value of the fitness function.

Further on, a variant of this method is presented, in which the probability $p(i)$ that an individual is selected for reproduction is calculated with the next formula:

$$(7)\ \ p(i) = \frac{1}{j}\left(\phi - 2\frac{\phi - 1}{j - 1}(i - 1)\right)\ ; \qquad 1 < \phi \leq 2\ ,$$

where j is the number of individuals in the population, i, $i = 1, \ldots, j$ is the position of that individual in the rank, and ϕ is a parameter called selection pressure. In a genetic algorithm in which the entire population is replaced in each generation, the expected value of the selections number of an individual is:

$$(8)\ \ E(i) = j \cdot p(i) = \phi - 2\frac{\phi - 1}{j - 1}(i - 1)$$

So, the expected value of the selections number of the best-ranked individual is $E(1) = \phi$. In genetic algorithms, through the recombination of the genetic information of two parents, it results two offspring, so $E(i)$ is also the expected value of the number of offsprings of the individual that has the i position in the rank. In figure 3 the function $E(i)$ is presented:

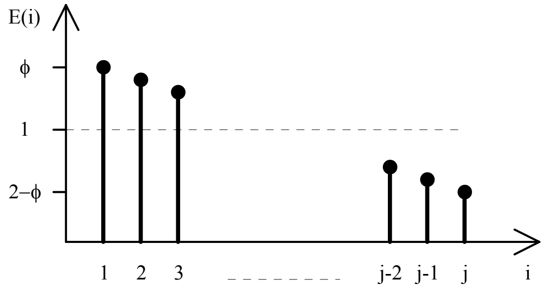

Figure 3. The expected value of the number of offsprings, in a SGA.

About the ranking selection method it can be stated that:

- The method can be successfully applied both in maximum and minimum type problems;
- The selection pressure, "a qualitative indicator used in understanding how the genetic algorithm works", is in this case a "control parameter of the genetic algorithm";
- In the presence of a super-individual in the population, the ranking selection method gives better results than the proportional selection method.

In a genetic algorithm, a small selection pressure occurs in two cases: when the population is degenerate or the objective function is of type flat top. The unique disadvantage of the ranking selection method is that the genetic finds a champion even if it isn't necessary, that is the case when the selection pressure is too small.

4. MATHEMATICAL MODELS FOR THE JFET

This problem is a very interesting one, because the JFET has two mathematical models: an analytic one and an empirical one that cannot be inferred one from the other. The analytic model of the JFET, presented in Grove (1967) or in Dascălu (1982) is:

$$I_D = \frac{G_0}{3}\Bigg(V_{DS} - \frac{2}{3}\cdot\frac{(\Phi_0 - V_{GS} + V_{DS})^{3/2}}{(\Phi_0 - V_P)^{1/2}} + \frac{2}{3}\cdot\frac{(\Phi_0 - V_{GS})^{3/2}}{(\Phi_0 - V_P)^{1/2}}\Bigg), \tag{9}$$

so it is a two places function $I_D = f(V_{GS}, V_{DS})$, that has three model parameters:

- Φ_0 - the potential internal difference of the command junction;
- V_P - the channel closing voltage;
- G_0 - the channel initial conductance.

The parameter Φ_0 depends on the manufacturing technology of the command junction. For silicon pn junction the internal potential difference of the command junction is $\Phi_0 = 0.7\cdots0.9\ \text{V}$, so it takes values in a restrained interval.

The parameters V_P and G_0 depend both on the manufacturing technology of the command junction and on the transistor geometry. The parameter V_P can be experimentally determined. The parameter G_0 is more difficult to access experimentally, so the initial channel conductance is evaluated, in conditions that $V_{GS} = 0$ and $V_{DS} = -V_P$, from the equation:

$$I_{DSS} = \frac{G_0}{9}\left(V_P - 2\Phi_0 + 2\frac{\Phi_0^{3/2}}{(\Phi_0 - V_P)^{1/2}}\right), \tag{10}$$

where I_{DSS} is a measurable parameter called saturation current.

The model (9) is valid for $V_{DS} < V_{GS} - V_P$, that is for the curved zone of the output characteristic, called "triode zone". The zone where the output characteristics are parallel with the abscissa is called "pentode zone". The limit between the triode zone and the pentode zone is calculated substituting $V_{GS} = V_{DS} + V_P$ in the model (9) and is:

$$I_D = \frac{G_0}{9}\Bigg(3V_{DS} - 2\Phi_0 + 2V_P + 2\frac{(\Phi_0 - V_P - V_{DS})^{3/2}}{(\Phi_0 - V_P)^{1/2}}\Bigg). \tag{11}$$

Substituting $V_{DS} = V_{GS} - V_P$ in the model (9) the analytic model of the transfer characteristic $I_D = f(V_{GS})$ is obtained:

$$I_D = \frac{G_0}{9}\Bigg(3V_{DS} - 2\Phi_0 + 2V_P + 2\frac{(\Phi_0 - V_{GS})^{3/2}}{(\Phi_0 - V_P)^{1/2}}\Bigg). \tag{12}$$

Given a JFET with $I_{DSS} = 8\ \text{mA}$, $V_P = -2.5\ \text{V}$ and $\Phi_0 = 0.8\ \text{V}$. In figure 4 with the function (12) the transfer function was plotted, with the function (9) there were plotted the output characteristics for $V_{GS} = -k\cdot 0.5\ \text{V}$, $k = 0,\ldots,4$, and with the function (11) the limit between the triode zone and the pentode zone was plotted.

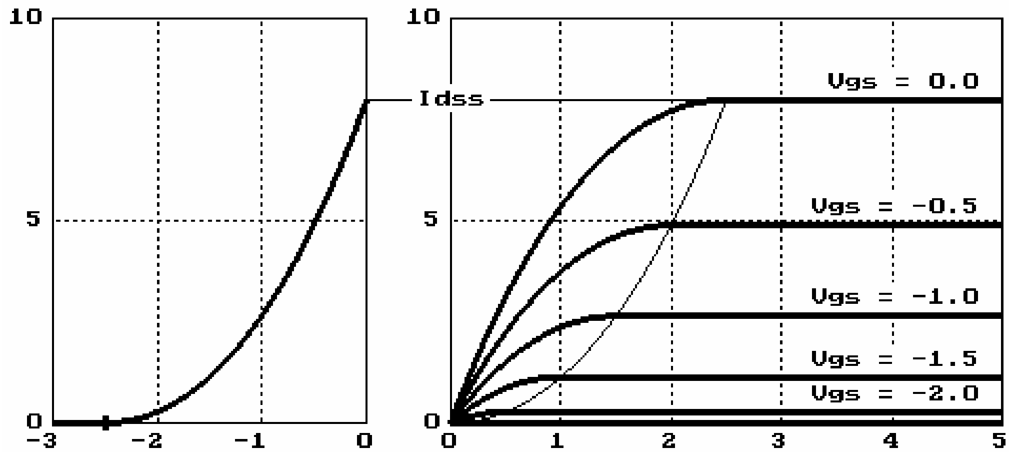

Figure 4. The JFET characteristics

The empirical model has the expression:

$$(13)\quad I_D = I_{DSS}\left(1-\frac{V_{GS}}{V_P}\right)^2$$

and it is a tangent parabola to the abscissa in the point V_P, that intersects the ordinate in the point I_{DSS}. It can be noticed that the empirical model has a much simpler expression, it has only two parameters but it is valid only for a transfer characteristic measured for $V_{DS} \geq V_{GS} - V_P$ and for the pentode zone of the output characteristics.

5. EXPERIMENTAL RESULTS

The genetic algorithm was run in the next conditions:

- The population size: $N = 30$
- The number of new individuals in each generation: $M = 20$
- The elite group size: $E = 1$
- The mutation probability: $p_m = 0.05$
- The selection pressure: $\phi = 1.5$
- The gene length: $L = 10$ bits

The identification was made with two minimal quadratic error type objective functions:

$$(14)\quad \begin{array}{l} x^e(i) = \left[I_{DSS}(i), V_P(i)\right]^T \\ x^a(i) = \left[I_{DSS}(i), V_P(i), \phi_0(i)\right]^T \end{array}$$

$$(15)\quad f^*(i) = \sum_{n=1}^{12}\left[I_D^m(n) - I_D^*\left(V_{DS}^m(n); x^*(i)\right)\right],$$

where $f^e(i)$ is the objective function of the empirical model, $f^a(i)$ is the objective function of the analytic model, $i = 1,\ldots,30$ is the individual index, $I_{DSS}(i)$, $V_P(i)$ and $\Phi_0(i)$ are the model parameters obtained decoding the individual genes, and $\left(I_D^m(n), V_{DS}^m(n)\right)$, $n = 1,\ldots,12$, are the 12 pairs of values experimentally determined on whose basis the identification was made.

The transform of the objective function was made with transform (5), with the parameters experimentally obtained $c = 1$, I $C = 0.3$ and with the ranking selection method (transform 6) where the selection pressure was considered $\phi = 1.5$.

In figure 5 it is plotted through dots the datum from whom the parametric identification has started, and with a continuous line it is plotted the transfer characteristic obtained from the parametric identification. In the left it is plotted the empirical model result, and in the right the analytic model result. It can be noticed that, both fort the empirical model and for the analytic one the input data are matching very well with the identification result.

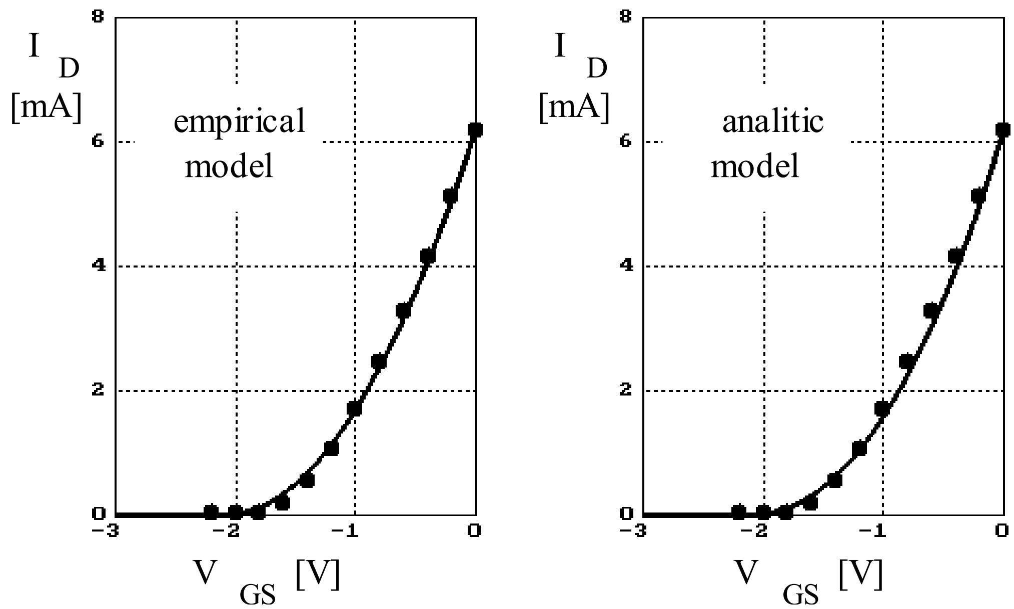

Figure 5. A comparison between the JFET transfer characteristic obtained from identification and the one experimentally determined

i	V_{GS}^m [V]	I_D^m [mA]	$I_D^a - I_D^m$ [mA]	$I_D^a - I_D^m$ [mA]
1	0	6.21	0.12	0.14
2	-0.02	5.15	0.02	-0.01
3	-0.04	4.19	-0.06	-0.10
4	-0.06	3.31	-0.10	-0.15
5	-0.08	2.47	-0.07	-0.10
6	-0.10	1.73	-0.02	0.03
7	-0.12	1.10	0.04	0.05
8	-0.14	0.59	0.09	0.12
9	-0.16	0.22	0.12	0.16
10	-0.18	0.07	0.05	0.08
11	-0.20	0.05	-0.04	0.02
12	-0.22	0.05	-0.05	-0.05

Table 1. A comparison between the errors of the empirical model and the analytic model

In table 1 there are presented the measured data from which the identification was started and the errors between the two models of the JFET:

- V_{GS}^m = the measured grid-source voltage
- I_D^m = the measured drain current
- $I_D^e - I_D^m$ the empirical model error
- $I_D^a - I_D^m$ the analytic model error

In the table 2 there are comparatively presented the parameters values obtained after the running of the genetic algorithm over the two models, and in the last line it is presented the modeling error calculated with the formulae $I_D = I_D^e(n)$ $I_D = I_D^a(n)$

$$\text{(16)} \quad \sigma = \sqrt{\frac{1}{12} \sum_{n=1}^{12} \left[I_D^m(n) - I_D(n) \right]}$$

At first sight, both the empirical model and the analytic model give very good results. At a closer look, it can be noticed that $\Phi_0 = 1.4\,\text{V}$ an artificial value because for silicium the width of the forbidden band is $W_c - W_c = 1.1\,\text{eV}$, so, in consequence, $\Phi_0 < 1.1\,\text{V}$. The internal potential difference, Φ_0, can be calculated, if there are known the impurity concentrations from the junction’s p and n zones, and if there are known the energetic values introduced by the impurities. For a silicium pn junction, the typical value of the potential difference value is $\Phi_0 = 0.7 \cdots 0.9\ \text{V}$.

6. CONCLUSIONS

The JFET physical parameters’ identification leads to the following conclusions:

- In the calculations that refer to the “pentode zone” of the JFET characteristics, the empirical model (12) is more precise than the analytic one (8). Moreover, the empirical model is easier to use because it is a simple analytic function. The typical application in which the transistor works in the pentode zone is the JFET small signal amplifier.

- The empirical model is not valid in the "triode zone" of the JFET characteristics, where the analytic model is used. The typical application in which the JFET works in the triode zone is the use of the transistor as "voltage-steered resistor"
- The tabled data set is valid only in the output characteristics pentode zone. Starting from this data set, the Φ_0 parameter identification is irrelevant maybe because the analytic model sensitivity is very little depending on the parameter Φ_0. In this case, it is reasonable to choose $\Phi_0 = 0.8$ V and to identify only two parameters I_{DSS} and V_P.

The genetic algorithm minimizes very well any of the functions (13), no matter if the formula (5) or the ranking selection method (6) is used for the transform of the objective function in an adjustment one. In figure 6 it is presented the shape of the adjustment function $f^e(x)$ represented with the curve levels $f^e(x) = 1$, $f^e(x) = 3$ and $f^e(x) = 5$, calculated for the input data set from table 1.

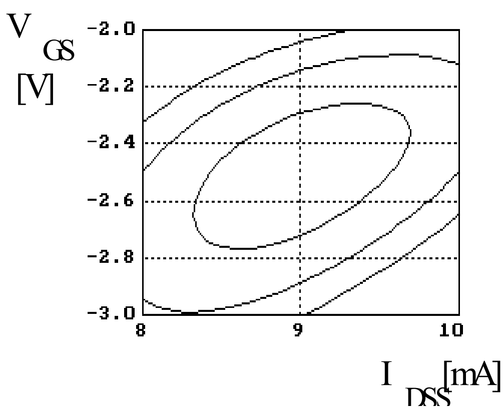

Figure 6. The shape of the adjustment function $f^e(x)$

The objective functions (12) and $f^a(x)$ (13) have too complicated expressions to be used by a derivative optimization method. In this way, it is justified the use of a seeking method, but the shape of the objective function from figure 6 isn't too complicated, and it is expected that another methods like the relaxation method or the bit-climbing algorithm should also find the correct result.

REFERENCES

Goldberg D. E. (1991). Genetic Algorithms. Addison-Wesley Usa, (15767), 1991. Translated in French, Copyright © Juin 1994 Editions Addison-Wesley France, S. A.

Michalewicz Z. (1994). Genetic Algorithms + Data Structures = Evolution Programs. © springer-Verlag Berlin Heidelberg 1994.

Witley D., K. Mathias, and L. Pyeatt (1995). Hyperplane ranking in simple genetic algorithms. In L. Eshelman (Ed.), Proceedings of the Sixth International Conference on Genetic Algorithms. Morgan Kaufmann.

Maclay D. and R. Dorey (1995). Applying genetic Search Techniques to Drivetrain Modeling. IEEE Control Systems, Vol. 13 no. 3 June 1995.

Bastien A. (1997). Adaptive genetic Programming for System Identification. EUFIT 97, September 8-11, 1997, Aachen, Germany p. 759-763.

Kristinnson K. and G. A. Durmont (1992). System Identification and Control Using Genetic Algorithms. IEEE Transactions on Man, and Cybernetics, vol. 22, no. 5, September 1992, 1033-1046.

Grove A. S. (1967). Fizica şi tehnologia dispozitivelor electronice. Editura tehnică, Bucureşti, 1973. Translated from "Physics and Technology of Semiconductor Devices", 1967, Jhohn Wiley & Sons.

Dascălu D. (1982). Dispozitive şi circuite electronice. Editura didactică şi pedagogică, Bucureşti, 1982.