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Estimation of the parameters of metal oxide gapless surge arrester equivalent circuit models using genetic algorithm

C.A. Christodoulou, I.F. Gonos*, I.A. Stathopulos

High Voltage Laboratory, School of Electrical and Computer Engineering, National Technical University of Athens, 9 Iroon Politechniou Str., Zografou Campus, Athens GR 15780, Greece

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ABSTRACT

In the present work a genetic algorithm is developed, for the evaluation of the parameters of metal oxide gapless surge arrester circuit models, in order to minimize the error between the computed and the measured (by the manufacturer) peak value of the residual voltage for each given current waveform and level separately. Furthermore, the algorithm is modified in order to minimize the error simultaneously for all the given injected impulse (lightning and switching) current curves.

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1. Introduction

The adequate circuit representation of metal oxide gapless surge arresters and the selection of their circuit parameters are significant issues for lightning and switching overvoltage performance studies. Metal oxide gapless surge arresters cannot be modeled only as non-linear resistances, since their response, i.e. their residual voltage for a given current, is a function of the magnitude and the slope of the injected pulse. Many researchers have presented appropriate circuit models [1–4], in order to predict the arrester residual voltage for a given injected current impulse. The accuracy of the results is strongly depended on the adjustment of the parameter values, for each model. For this reason, various iteration methods have been applied [5–8], in order to determine the parameter values that minimize the error between the computed and the manufacturer's residual voltage, adjusting the parameter values of each equivalent circuit model for one current level and waveform each time. In the current paper, a genetic algorithm is developed and is applied to each model, for each given injected impulse (lightning or switching) current separately, and then for all the current levels simultaneously.

2. Surge arrester models

The most used equivalent circuit models, that reproduce adequately the arresters performance are:

- the IEEE model [2],
- the Pinceti–Giannettoni model [3],
- the Fernandez–Diaz model [4].

The IEEE Working Group 3.4.11 [2] proposes the model of Fig. 1(a), including the non-linear resistances A_0 and A_1, separated by a *R-L* filter. For slow front injected surges the filter impedance is low and the non-linear resistances are in parallel. For fast front surges the filter impedance becomes high, and the current flows through the non-linear resistance A_0.

The other two models are simpler forms of the IEEE model. The Pinceti–Giannettoni model [3] has no capacitance and the resistances R_0 and R_1 are replaced by one resistance at the input terminals, as shown in Fig. 1(b). The non-linear resistors are based on the curves of [2]. In the Fernandez–Diaz model [4] A_0 and A_1 are separated by L_1, while L_0 is neglected (Fig. 1(c)). C is added in arrester terminals and represents terminal-to-terminal capacitance of the arrester. The computation of the parameters for each circuit model is performed according to the procedures described in [2], [3] and [4], correspondingly.

The simulation of each model is performed, solving the state equations for each non linear equivalent circuit model [5,8], using

* Corresponding author. Tel.: +30 2107723539; fax: +30 2107723504.
E-mail address: igonos@ieee.org (I.F. Gonos).

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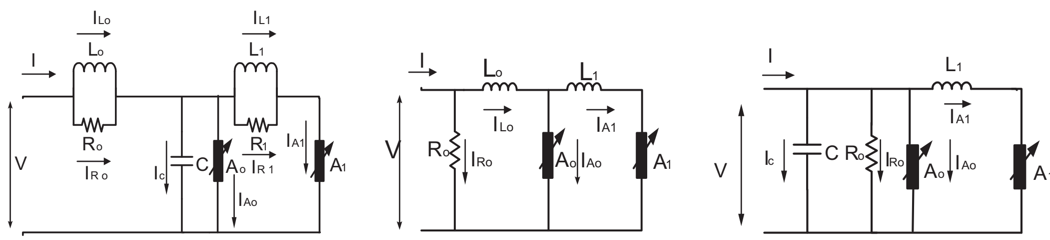

Fig. 1. (a) The IEEE model [2], (b) the Pinceti–Giannettoni Model [3], and (c) the Fernandez–Diaz Model [4].

appropriate computer program. The two non linear resistors A_0 and A_1 are represented by piecewise linear functions:

$$V_{A_0} = aI_{A_0} + b \quad (1)$$

$$V_{A_1} = AI_{A_1} + B \quad (2)$$

Analytically, for the IEEE model:

$$\frac{L_0}{R_0} \cdot \frac{dI_{L_0}}{dt} = I - I_{L_0} \quad (3)$$

$$\frac{L_1}{R_1} \cdot \frac{dI_{L_1}}{dt} = I_{A_1} - I_{L_1} \quad (4)$$

$$C\frac{dV_{A_0}}{dt} = I - I_{A_0} - I_{A_1} \quad (5)$$

$$V = V_{A_0} + L_0\frac{dI_{L_0}}{dt} \quad (6)$$

For the Pinceti–Giannettoni model:

$$I = I_{R_0} + I_{L_0} \quad (7)$$

$$L_0\frac{dI_{L_0}}{dt} + V_{A_0} = V \quad (8)$$

$$I_{L_0} = I_{A_0} + I_{A_1} \quad (9)$$

$$V_{A_0} = L_1\frac{dI_{A_1}}{dt} + V_{A_1} \quad (10)$$

$$V = (I - I_{L_0}) \cdot R_0 \quad (11)$$

For the Fernandez–Diaz model:

$$I = I_C + I_R + I_{A_0} + I_{A_1} \quad (12)$$

$$C\frac{dV}{dt} + \frac{V}{R_0} = I - I_{A_0} - I_{A_1} \quad (13)$$

$$L_1\frac{dI_{A_1}}{dt} = V_{A_1} - V_{A_0} \quad (14)$$

$$I_{A_0} = \frac{V - b}{a} \quad (15)$$

$$V = I_{R_0} \cdot R_0 \quad (16)$$

3. Application of the genetic algorithm for each current level

Genetic algorithms are widely applied in science and engineering, for solving practical search and optimization problems. In the current work an appropriate genetic algorithm is applied, in order to adjust the parameter values of each arrester model, that minimize the relative error between the predicted, from each model, residual voltage for an injected impulse current and the residual voltage given in manufacturer's datasheet, for each current level separately. The same algorithm gives excellent results in several other optimization problems [9–11]. The optimization error function that was used by the developed genetic algorithm, in order to receive best values for the related parameters of the arrester, is Eq. (17):

$$e = \left| \frac{V_c(x)_{I,T_1/T_2} - V_{m,I,T_1/T_2}}{V_{m,I,T_1/T_2}} \right| \quad (17)$$

where:

$V_c(x)_{I,T_1/T_2}$ is the peak value of the computed residual voltage for a given injected impulse current (I the peak current, T_1 the rise time and T_2 the time-to-half value of the impulse current);
$V_{m,I,T_1/T_2}$ is the measured by the manufacturer residual voltage for a given injected impulse current (I the peak current, T_1 the rise time and T_2 the time-to-half value of the impulse current);
x is a column vector containing the parameters x_1, x_2, ..., x_n of each one model:

for the IEEE model [2]

$$x = [x_1, x_2, x_3, x_4, x_5]^T = [R_0, R_1, L_0, L_1, C]^T \quad (18)$$

for the Pianceti–Giannettoni model [3]

$$x = [x_1, x_2, x_3]^T = [R_0, L_0, L_1]^T \quad (19)$$

for the Fernandez–Diaz model [4]

$$x = [x_1, x_2, x_3]^T = [R_0, L_1, C]^T \quad (20)$$

A simple genetic algorithm relies on the processes of:

- reproduction,
- crossover, and
- mutation

to reach the global or "near-global" optimum. To start the search, genetic algorithms require the initial set of the points P_s, which called population, analogous to the biological system. A random number generator creates the initial population. This initial set is converted to a binary system and is considered as chromosomes, actually sequences of "0" and "1".

The next step is to form pairs of these points that will be considered as parents for a reproduction. Parents come to reproduction and interchange N_p parts of their genetic material. This is achieved by crossover.

After the crossover there is a very small probability P_m for mutation. Mutation is the phenomenon where a random "0" becomes "1" or a "1" becomes "0". Assume that each pair of "parents" gives rise to N_c children. Thus the genetic algorithm generates the initial layouts and obtains the objective function values. The above operations are carried out and the next generation with a new population of strings is formed. By the reproduction, the population of the "parents" is enhanced with the "children", increasing the original population since new members are added. The parents always belong to the considered population. The new population has now $P_s + N_c \cdot P_s/2$ members.

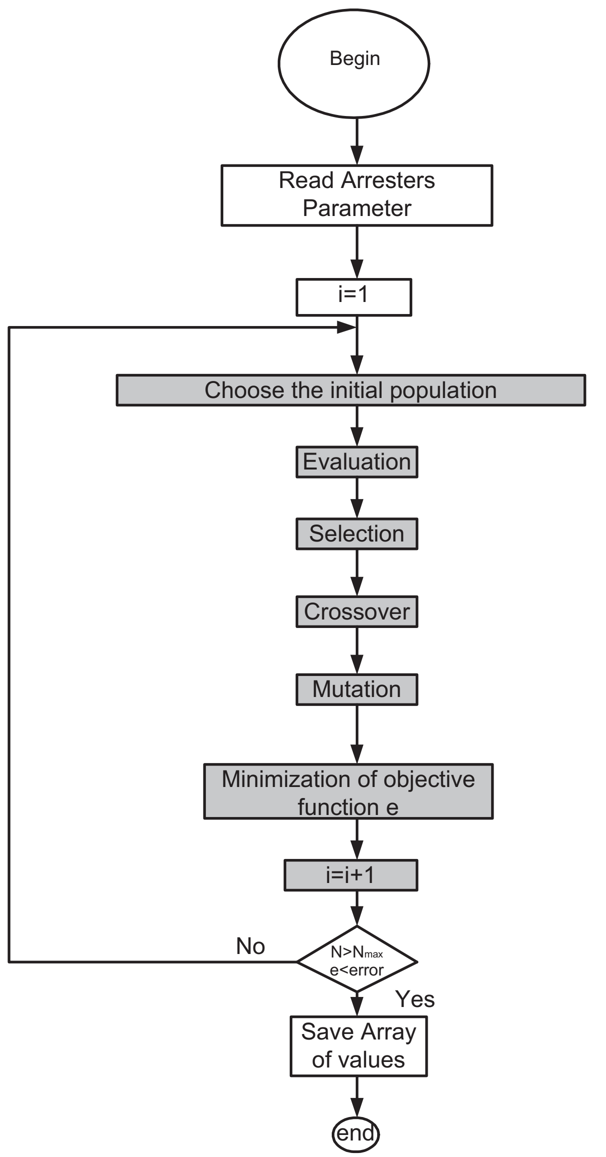

Fig. 2. Flow chart of the genetic algorithm.

Then the process of natural selection is applied. According to this process only P_s members survive out of the $P_s + N_c{\cdot}P_s/2$ members. These P_s members are selected as the members with the lower values of e, since a minimization problem is solved.

Repeating the iterations of reproduction under crossover and mutation and natural selection genetic algorithms can find the minimum of e. The best values of the population converge at this point. The termination criterion is fulfilled if either the mean value of e in the P_s-member population is no longer improved or the number of iterations is greater than the maximum number of iterations N_{max}. Briefly, in Fig. 2, the basic function of the algorithm is shown.

Table 1 presents the electrical and physical characteristic data of the examined surge arrester.

Tables 2–6 show the initial computed parameters for each one model, according to the procedures described in [2–4], as well as the optimum parameter values obtained using the genetic algorithm, for each lightning or switching impulse current level separately, and the corresponding computed residual voltage peak value.

Table 1
Electrical and insulation data of the examined arrester.

Maximum continuous operating voltage		12 kV
Rated voltage		15 kV
Nominal discharge current		10 kA
Maximum residual voltage with lightning current 8/20 μs	5 kA	36.72 kV
	10 kA	38.88 kV
	20 kA	43.37 kV
Maximum residual voltage with switching current 30/60 μs	125 A	29.05 kV
	500 A	31.06 kV
Height		183 mm
Insulation material		Silicon rubber

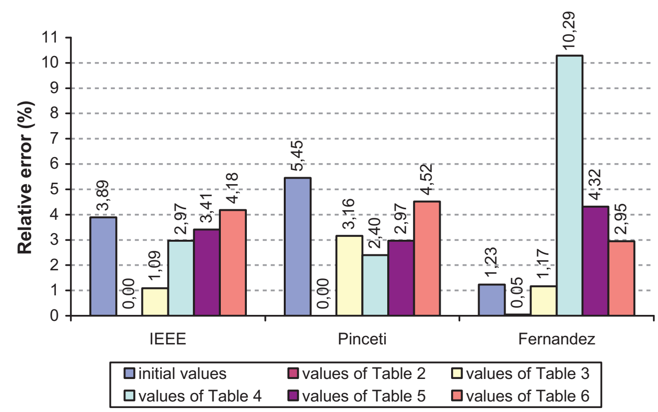

Fig. 3. Relative error for a 5 kA (8/20 μs) injected impulse current using the initial values and the values of Tables 2–6.

4. Application of the genetic algorithm for all given current levels

The application of the developed genetic algorithm, separately for each current level, gives accurate results, reducing almost to zero the objective function. However, in Figs. 3–7, where are presented the relative errors of the computed residual voltage using the initial parameter values and those obtained from the genetic algorithm (for each current level separately), it is obvious that the parameter values that minimize the error for a current waveform may increase the error for the other injected surge pulses.

In order to compute these parameter values of each circuit model, that guarantee the simultaneous reduce of the relative error for the five current levels, the developed genetic algorithm is modified. The new objective function is:

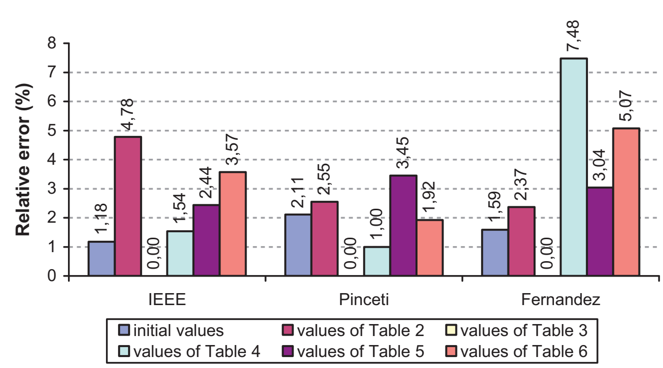

Fig. 4. Relative error for a 10 kA (8/20 μs) injected impulse current using the initial values and the values of Tables 2–6.

Table 2
Parameters and residual voltage peak values for an injected impulse current 5 kA (8/20 μs).

5 kA (8/20 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	98.12 Ω	1 MΩ	0.873 MΩ	1 MΩ	0.639 MΩ
R_1	11.895 Ω	22.74 Ω	–	–	–	–
L_0	0.0366 μH	0.103 μH	0.049 μH	0.012 μH	–	–
L_1	2.745 μH	1.210 μH	0.148 μH	0.229 μH	0.349 μH	1.812 μH
C	546.45 pF	1154.7 pF	–	–	546.45 pF	2347.3 pF
$V_{c,5\,\text{kA}}$	38.15 kV	36.72 kV	34.72 kV	36.72 kV	36.27 kV	36.74 kV

Table 3
Parameters and residual voltage peak values for an injected impulse current 10 kA (8/20 μs).

10 kA (8/20 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	25.43 Ω	1 MΩ	0.895 MΩ	1 MΩ	1.465 MΩ
R_1	11.895 Ω	17.85 Ω	–	–	–	–
L_0	0.0366 μH	0.278 μH	0.049 μH	0.376 μH	–	–
L_1	2.745 μH	1.017 μH	0.148 μH	0.0435 μH	0.349 μH	1.371 μH
C	546.45 pF	967.21 pF	–	–	546.45 pF	675.50 pF
$V_{c,10\,\text{kA}}$	39.34 kV	38.88 kV	38.06 kV	38.88 kV	39.50 kV	38.88 kV

Table 4
Parameters and residual voltage peak values for an injected impulse current 20 kA (8/20 μs).

20 kA (8/20 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	42.97 Ω	1 MΩ	0.753 MΩ	1 MΩ	1.072 MΩ
R_1	11.895 Ω	55.49 Ω	–	–	–	–
L_0	0.0366 μH	0.019 μH	0.049 μH	0.692 μH	–	–
L_1	2.745 μH	31.24 μH	0.148 μH	0.037 μH	0.349 μH	1.811 μH
C	546.45 pF	1587.1 pF	–	–	546.45 pF	2601.3 pF
$V_{c,20\,\text{kA}}$	39.38 kV	43.42 kV	44.63 kV	43.37 kV	39.75 kV	43.39 kV

Table 5
Parameters and residual voltage peak values for an injected impulse current 125 A (30/60 μs).

125 A (30/60 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	34.72 Ω	1 MΩ	0.705 MΩ	1 MΩ	0.520 MΩ
R_1	11.895 Ω	8.72 Ω	–	–	–	–
L_0	0.0366 μH	0.057 μH	0.049 μH	0.064 μH	–	–
L_1	2.745 μH	2.021 μH	0.148 μH	0.362 μH	0.349 μH	0.241 μH
C	546.45 pF	817.92 pF	–	–	546.45 pF	725.91 pF
$V_{c,20\,\text{kA}}$	30.20 kV	29.05 kV	27.73 kV	29.05 kV	30.86 kV	29.05 kV

$$e = \left|\frac{V_c(x)_{5\,\text{kA},8/20\,\mu\text{s}} - V_{m,5\,\text{kA},8/20\,\mu\text{s}}}{V_{m,5\,\text{kA},8/20\,\mu\text{s}}}\right| + \left|\frac{V_c(x)_{10\,\text{kA},8/20\,\mu\text{s}} - V_{m,10\,\text{kA},8/20\,\mu\text{s}}}{V_{m,10\,\text{kA},8/20\,\mu\text{s}}}\right| + \left|\frac{V_c(x)_{20\,\text{kA},8/20\,\mu\text{s}} - V_{m,20\,\text{kA},8/20\,\mu\text{s}}}{V_{m,20\,\text{kA},8/20\,\mu\text{s}}}\right| + \left|\frac{V_c(x)_{125\,\text{A},30/60\,\mu\text{s}} - V_{m,125\,\text{A},30/60\,\mu\text{s}}}{V_{m,125\,\text{A},30/60\,\mu\text{s}}}\right| + \left|\frac{V_c(x)_{500\,\text{A},30/60\,\mu\text{s}} - V_{m,500\,\text{A},30/60\,\mu\text{s}}}{V_{m,500\,\text{A},30/60\,\mu\text{s}}}\right| \quad (21)$$

where:

$V_c(x)_{5,10,20\,\text{kA},8/20\,\mu\text{s}}$ is the peak value of the computed residual voltage for each current level (5, 10, 20 kA) for a 8/20 μs injected current waveform;
$V_c(x)_{125,500\,\text{A},30/60\,\mu\text{s}}$ is the peak value of the computed residual voltage for each current level (125, 500 A) for a 30/60 μs injected current waveform;
$V_{m,5,10,20\,\text{kA},8/20\,\mu\text{s}}$ is the measured by the manufacturer residual voltage for each current level (5, 10, 20 kA) for a 8/20 μs injected current waveform;

Table 6
Parameters and residual voltage peak values for an injected impulse current 500 A (30/60 μs).

500 A (30/60 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	52.31 Ω	1 MΩ	0.924 MΩ	1 MΩ	0.871 MΩ
R_1	11.895 Ω	39.57 Ω	–	–	–	–
L_0	0.0366 μH	1.049 μH	0.049 μH	0.257 μH	–	–
L_1	2.745 μH	1.225 μH	0.148 μH	0.093 μH	0.349 μH	0.215 μH
C	546.45 pF	780.28 pF	–	–	546.45 pF	472.04 pF
$V_{c,20\,\text{kA}}$	32.58 kV	31.06 kV	29.17 kV	31.06 kV	32.71 kV	31.06 kV

Table 7
Optimized parameters for each model after the application of the genetic algorithm for all the injected impulse current waveforms simultaneously.

5, 10, 20 kA (8/20 μs) 125, 500 A (30/60 μs)	IEEE		Pinceti		Fernandez	
	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters	Initial parameters	Optimized parameters
R_0	18.30 Ω	60.47 Ω	1 MΩ	1.249 MΩ	1 MΩ	0.891 MΩ
R_1	11.895 Ω	19.23 Ω	–	–	–	–
L_0	0.0366 μH	0.512 μH	0.049 μH	0.108 μH	–	–
L_1	2.745 μH	1.524 μH	0.148 μH	0.094 μH	0.349 μH	0.254 μH
C	546.45 pF	974.62 pF	–	–	546.45 pF	327.58 pF
$V_{c,5\,\mathrm{kA}}$	38.15 kV	35.67 kV	34.72 kV	37.55 kV	36.27 kV	36.87 kV
$V_{c,10\,\mathrm{kA}}$	39.34 kV	39.18 kV	38.06 kV	38.29 kV	39.50 kV	38.40 kV
$V_{c,20\,\mathrm{kA}}$	39.38 kV	41.50 kV	44.63 kV	42.78 kV	39.75 kV	41.35 kV
$V_{c,125\,\mathrm{A}}$	30.20 kV	29.94 kV	27.73 kV	29.90 kV	30.86 kV	30.12 kV
$V_{c,500\,\mathrm{A}}$	32.58 kV	32.28 kV	29.17 kV	32.37 kV	32.71 kV	30.31 kV

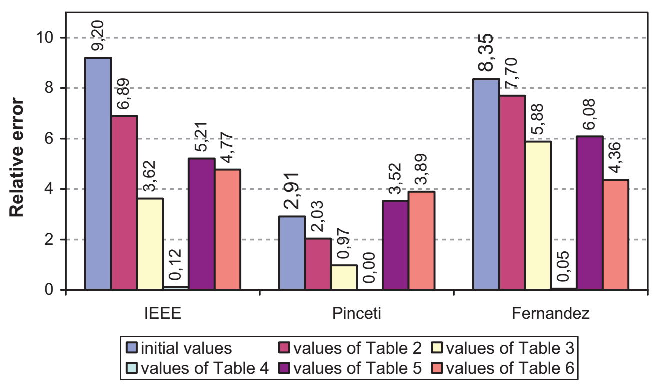

Fig. 5. Relative error for a 20 kA (8/20 μs) injected impulse current using the initial values and the values of Tables 2–6.

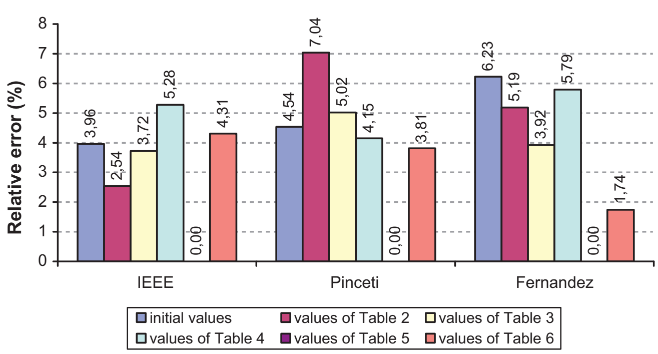

Fig. 6. Relative error for a 125 A (30/60 μs) injected impulse current using the initial values and the values of Tables 2–6.

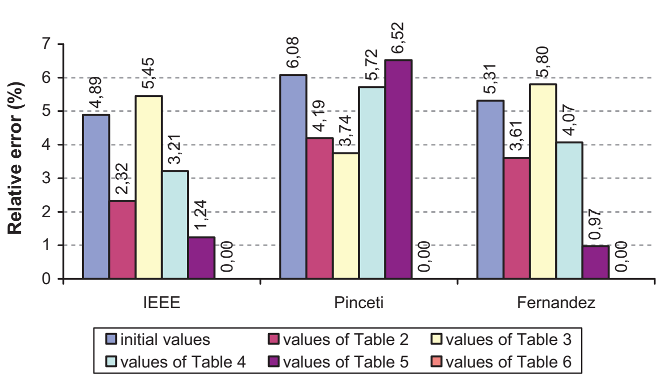

Fig. 7. Relative error for a 500 A (30/60 μs) injected impulse current using the initial values and the values of Tables 2–6.

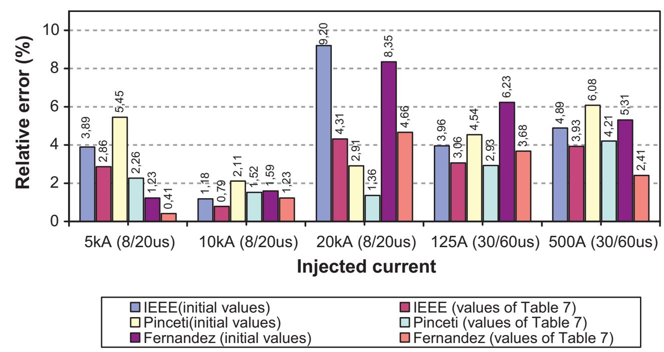

Fig. 8. Relative error for all the injected impulse current waveforms using the initial values and the values of Table 7.

$V_{m,125,500\,\mathrm{A},30/60\,\mu\mathrm{s}}$ is the measured by the manufacturer residual voltage for each current level (125, 500 A) for a 30/60 μs injected current waveform; and
x is a column vector containing the parameters $x_1, x_2, \ldots, x_n$ of each one model.

The obtained parameter values and the computed residual voltage peak values are presented in Table 7.

Fig. 8 presents the relative error for all the models and current levels, using initial parameters and the parameters of Table 7. It is obvious that, the use of the parameters obtained from the application of the genetic algorithm simultaneously for the 5 kA (8/20 μs), 10 kA (8/20 μs), 20 kA (8/20 μs), 125 A (30/60 μs) and 500 A (30/60 μA), guarantees that the relative error will be reduced for all the five different injected currents.

5. Conclusions

The current work proposes a methodology, based on artificial intelligence techniques, for the surge arrester circuit models parameter values adjustment, that can be applied to the already existed and the equivalent circuit models to be proposed. For this scope, an appropriate genetic algorithm was developed, that gives as output the parameters of each arrester model that minimize the defined objective function, i.e. the error between the computed and the manufacturer's residual voltage for a given injected lightning or switching impulse current. Advantage of the developed genetic algorithm is that it adjusts the parameter values of each circuit model not only for one current level (as it is performed in [5–8]), but simultaneously for five different current peak values and waveforms (internal (30/60 μs) and external (8/20 μs) overvoltage curves), given by the manufacturer. The method gives accurate results, taking into account a wide range of the parameter values, in comparison to other compatible optimization methods (simplex, Powell, downhill, etc.), where the optimum solution is strongly depended on the initial values. The genetic algorithm examines the local minima and extracts the best solution, in contrast to the other methods that can be 'trapped' to a local minimum. The developed genetic algorithm analyzes the possible combinations of the parameter values for each model, resulting in the best solution that reduces the objective function. Additionally, the algorithm is flexible, since the user can choose the speed of the simulation and the desired accuracy, selecting the range of the values parameters, the number of parents and the iteration number.

Firstly, the method was applied for each current level separately, eliminating the error between the theoretical and measured residual voltage peak values. The algorithm was modified in order to compute the optimized parameters that minimize the relative error simultaneously for the five given current impulses. The circuit models, using these parameter values give satisfactory results, not for only one current level, but for a wider current range. The performed analysis and the obtained results prove the efficiency of the methodology and, additionally, it is shown that the already proposed models give satisfactory prediction of the residual voltage, if the appropriate values of their parameters are used, so there is no strong dependence on the model that will be selected and there is no need for a new equivalent model.

References

[1] B. Zitnik, M. Zitnik, M. Babuder, The ability of different simulation models to describe the behavior of metal oxide varistors, in: 28th International Conference on Lightning Protection, Paper VII–11, Kazanawa, Japan, September 18–22, 2006.

[2] IEEE Working Group 3.4.11, Modeling of metal oxide surge arresters, IEEE Transactions on Power Delivery 7 (1) (1992) 302–309.

[3] P. Pinceti, M. Giannettoni, A simplified model for zinc oxide surge arresters, IEEE Transactions on Power Delivery 14 (2) (1999) 393–398.

[4] F. Fernandez, R. Diaz, Metal oxide surge arrester model for fast transient simulations, in: International Conference on Power System Transients IPST'01, Paper 14, Rio De Janeiro, Brazil, June 24–28, 2001.

[5] H.J. Li, S. Birlasekaran, S.S. Choi, A parameter identification technique for metal-oxide surge arrester models, IEEE Transactions on Power Delivery 17 (3) (2002) 736–741.

[6] M.C. Margo, M. Giannettoni, P. Pinceti, Validation of ZnO surge arresters model for overvoltage studies, IEEE Transactions on Power Delivery 19 (4) (2004) 1692–1695.

[7] B. Abdelhafid, Parameter identification of ZnO surge arrester models based on genetic algorithms, Electric Power Systems Research 78 (2008) 1204–1209.

[8] P.F. Evangelides, C.A. Christodoulou, I.F. Gonos, I.A. Stathopulos, Parameters' selection for metal oxide surge arresters models using genetic algorithm, in: 30th International Conference on Lightning Protection, Paper 9C-1315, Cagliari, Italy, September 13–17, 2010.

[9] I.F. Gonos, F.V. Topalis, I.A. Stathopulos, A genetic algorithm approach to the modelling of polluted insulators, IEE Proceedings Generation, Transmission and Distribution 149 (3) (2002) 373–376.

[10] I.F. Gonos, I.A. Stathopulos, Estimation of multi-layer soil parameters using genetic algorithms, IEEE Transactions on Power Delivery 20 (1) (2005) 100–106.

[11] G.P. Fotis, I.F. Gonos, F.E. Assimakopoulou, I.A. Stathopulos, Applying genetic algorithms for the determination of the parameters of the electrostatic discharge current equation, Institute of Physics Publishing, Measurement, Science and Technology 17 (10) (2006) 2819–2827.