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**Regular paper**

# Parameters Calculation of ZnO Surge Arrester Models by Genetic Algorithms

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*This paper proposes to provide a new technique based on the genetic algorithm to obtain the best possible series of values of the parameters of the ZnO surge arresters models. The validity of the predicted parameters is then checked by comparing the results predicted with the experimental results available in the literature. Using the ATP-EMTP package an application of the arrester model on network system studies is presented and discussed.*

**Keywords:** Surge arrester, ZnO, Models Genetic Algorithm**.**

## 1. INTRODUCTION.

The correct and adequate modeling of the characteristics of ZnO surge arresters is very important for insulation coordination studies and systems reliability. In the case of switching surge studies, the surge arresters can be represented with their non-linear V-I characteristic [1 — 3]. However, such a practice would not be suitable for lightning surge studies with fast front waves. This is due to the fact that the surge arresters behave differently in the presence of a fast disturbance. Typically, the residual voltage predicted for an impulse current having a front time equal to 1µs is 6–10% higher than that predicted for an impulse current having a front time equal to 8µs. For longer times to crests between 45 and 60 µs, the voltage is 2 to 4% lower than that due to an impulse current having a times to crests of 8µs [1 — 10].

With an aim of reproducing the dynamic characteristics of ZnO surge arresters mentioned previously, many researchers [1 — 8] addressed considerable efforts to the development of models of surge arresters. The authors in reference [1] recommend a model based on their database for fast transient currents ($T_f$ = 0.5 to 45µs). To determine model parameters, an iterative procedure try-error was proposed to reasonably reproduce the amplitude of the voltage obtained for a current wave 8/20 µs. To determine the values of the starting parameters, expressions, utilizing the height and the number of columns of the surge arresters, for linear elements and two tables for the non-linear elements were proposed. The IEEE model was then simplified by the authors of reference [2]. These parameters are reported to the tests of currents 1/5µs and 8/20µs.

A comparative study of the various models suggested in the literature was made [9]. It was concluded that the difficulties with these models reside essentially in the calculation and the adjustment of their parameters. Recently an alternative having for objective the identification of the parameters of the models suggested in the references [1, 2, and 5] by using a traditional optimization method was proposed in [10]. The authors had represented the non-linear resistances by piecewise functions and consequently a linearization was adopted. The problem of optimization was solved in two stages with an aim of avoiding possible numerical oscillations of the predicted voltage.

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The present paper proposes to provide a new solution based on genetic algorithms to obtain the best possible series of values of the parameters of ZnO surge arresters models. Interfacing the genetic algorithm with the ATP-EMTP was done to facilitate the calculation of the predicted voltage waveforms. The validity of the predicted parameters is then verified by comparing the predicted results with the experimental results available in the literature.

## 2. FORMULATION OF THE PROBLEM.

A typical simplified circuit of the measurement setup to test ZnO surge arresters is shown in figure 1. In this figure $V(t)$ is the voltage recorded at ZnO surge arresters terminals for an injected current $I(t)$ [11].

The response of a model can be correctly predicted, if an adequate choice of its parameters $x = (x_1,\ x_2,\dots,\ x_n)$ is done. These parameters can be determined by minimizing the following objective function:

$$\varepsilon = \int_0^T \ [V(t,x) - V_m(t)]^2 dt \tag{1}$$

In this equation:

$T$ : is the duration of the impulse current injected;

$V(t,x)$ : is the predicted residual voltage;

$V_m(t)$ : the measured residual voltage.

It is noted that a similar objective function was proposed in [10]. It contains an additional term (the weight function) used to accelerate the convergence of the traditional optimization algorithm suggested in this reference. Its determination required a certain experiment of numerical calculation. This weight function isn't necessary in the objective equation for the proposed genetic algorithm.

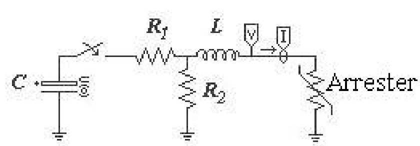



Figure 1. Typical measuring setup for ZnO surge arresters.

In its discrete form, the objective function (1) can be rewritten in the following way:

$$\varepsilon = \sum_{j=1}^{N} [V(j\Delta t,x) - V_m(j\Delta t)]^2 \Delta t \tag{2}$$

In this equation $N$ indicates the total number of discrete points; $\Delta T = T / N$ represents the computing time step. Moreover $x_j$ must be positive.

## 3. PROCEDURE OF OPTIMIZATION

The goal of the genetic algorithms (GA) is to optimize an objective function on a research space. For that, a population of individuals evolves according to an artificial

Darwinism (evaluation, selection, reproduction) based on the fitness F of each individual [12 — 15]. The fitness is directly related to the value of the objective function of this individual. Evolution Operators applied to the population allow to create new individuals (crossover and mutation) and to select the individuals of the population who will survive (selection and replacement). For parameters identification of a model whose structure is known, the individual is the set of the unknown parameters and consequently each gene coincides with a parameter.

The loop of the algorithm follows the following stages:

After a random initialization of the population the algorithm evaluates the function of adaptation of each individual.

*Stop criterion:* It is a criterion that allows stopping the process. One of the simple criteria often used is when the maximum number of generations is reached.

*Selection:* This operator selects among the parents those which will generate children.

*Creation of new individuals:* The creation of new individuals is done primarily using the operators of crossing and mutation. The crossover operator is an operator who combines parents to create one or more children. The mutation operator is an operator who modifies an individual to create another who is generally close to him.

The program used (figure 2) is an implementation of a genetic algorithm with real coding. An interfacing of this algorithm with the EMTP is carried out. In this program we use roulette wheel selection. The available crossovers are the multipoint and the barycentric crossover. Two mutations types are possible. The first is the Gaussian mutation with a constant variance or a decreasing variance during iterations. The second is a non-uniform mutation [13, 14]. The algorithm uses also the mutation depending on the distance suggested in [14]. This technique increases the probability of mutation of the children when the distance between the parents is small to avoid a premature convergence.

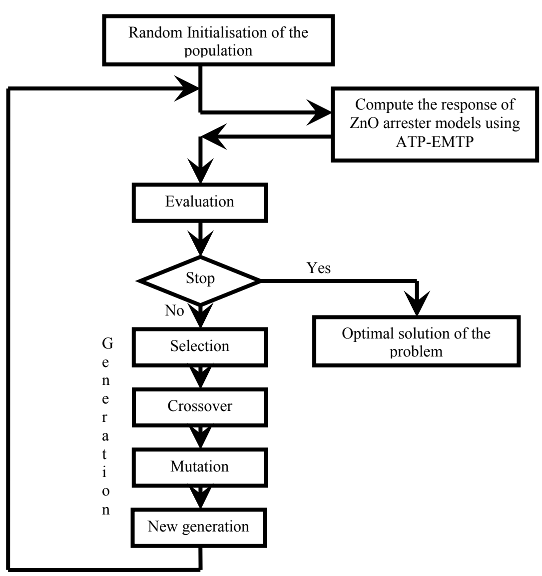



Figure 2. Stages of the genetic Algorithm

Technique of niching which consists in supporting the individuals who are far away from the other individuals, was introduced by increasing their fitness avoiding that all the population concentrates on a region of the search space. The elitism was also introduced by the algorithm. It ensures the decrease of the best value found during generations. Another technique, important for the correct operation of the algorithm, is the scaling. Several strategies of the scaling were tested among which we quote the scaling by the truncated sigma.

All these techniques increase the performances of the algorithm.

## 4. STATIC MODEL OF ZNO SURGE ARRESTER.

The developed genetic algorithm was subjected to a test to approximate the experimental data coming from manufacturers of surge arresters and compared with the method of least squares used by the ATP-EMTP. Experimental V-I characteristics of the surge arresters are generally modelled by a non-linear resistance whose variation is exponential [16]. By examining the results obtained shown in figure 3 we can conclude that the genetic Algorithm presents a good approximation of the experimental data of the manufacturers compared with those obtained by the ATP-EMTP.

## 5. DYNAMIC MODELS OF THE ZNO SURGE ARRESTERS.

In this section, the numerical method is applied to identify the parameters of the dynamic models of ZnO surge arresters. The selected examples come from the references [4, 5, 17, and 18]. The optimization is performed using the 8/20 µs current waveforms.

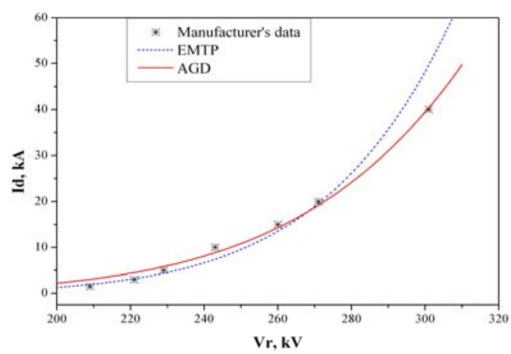
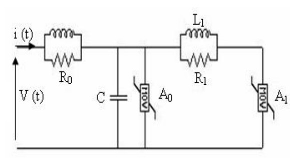



Figure 3. Comparison with the EMTP and the data of the manufacturers for surge arresters 108kV.

The models used in this investigation (figure 4) were proposed in [1, 2, 7, and 8]. In this paper they are noted Model 1, Model 2, Model 3 and Model 4 respectively. To ensure the convergence of the algorithm, adequate choice of the research interval of the parameters is necessary. During optimization the response of the model (waveforms) is computed by the EMTP and thereafter transferred to the genetic algorithm for the evaluation of the fitness. The parameters optimized for the various examples and models are listed in tables 1 to 4.

A discharge current $I(t)$ (10kA, 8/20µs) is applied to the models (Model 1, Model 2, Model 3, Model 4) with the optimal obtained parameters. The predicted voltage V (t) is compared with the experimental curves coming from references [4, 5, 17, and 18]. As it is shown in figures 5 to 8, all the models reproduce in an acceptable way the experimental characteristic.

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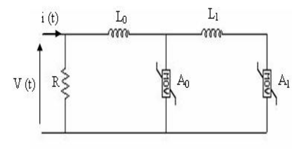


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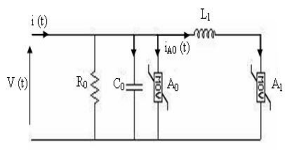


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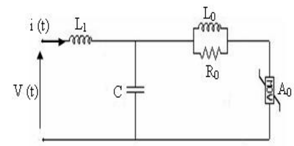


[12]

Figure 4. Used models.

Table 1: CASE OF MODEL 1

| Parameter | [4] | [5] | [17] | [18] |
|---|---|---|---|---|
| $R_0$ (Ω) | 0.453 | 0.781 | 0.634 | 0.892 |
| $R_1$ (Ω) | 0.655 | 1.102 | 0.924 | 0.181 |
| $L_0$ (μH) | 0.161 | 0.152 | 0.167 | 0.413 |
| $L_1$ (μH) | 0.091 | 3.854 | 4.850 | 0.437 |
| C (nF) | 1.040 | 1.031 | 1.245 | 0.959 |
| $p_0$ | 1.381 | 3.581 | 2.926 | 2.110 |
| $p_1$ | 4.710 | 3.651 | 3.673 | 2.313 |
| $q_0$ | 13.91 | 14.49 | 12.73 | 12.53 |
| $q_1$ | 8.080 | 9.104 | 8.609 | 7.033 |
| $V_{ref0}$ (kV) | 8.190 | 7.334 | 7.027 | 8.822 |
| $V_{ref1}$ (kV) | 7.501 | 7.135 | 7.286 | 7.353 |

Table 2: CASE OF MODEL 2

| Parameter | [4] | [5] | [17] | [18] |
|---|---|---|---|---|
| R (Ω) | 12.76 | 9.02 | 18.21 | 30.34 |
| $L_0$ (μH) | 0.021 | 0.019 | 0.022 | 0.069 |
| $L_1$ (μH) | 0.857 | 0.050 | 0.264 | 0.566 |
| $p_0$ | 2.616 | 7.137 | 3.535 | 2.240 |
| $p_1$ | 2.972 | 3.257 | 3.212 | 3.004 |
| $q_0$ | 11.30 | 11.70 | 11.53 | 10.25 |
| $q_1$ | 11.72 | 11.71 | 8.844 | 12.25 |
| $V_{ref0}$ (kV) | 7.631 | 9.157 | 7.758 | 10.81 |
| $V_{ref1}$ (kV) | 7.832 | 8.437 | 6.878 | 10.46 |

Table 3: CASE OF MODEL 3.

| Parameter | [4] | [5] | [17] | [18] |
|---|---|---|---|---|
| R (Ω) | 5.262 | 6.384 | 6.526 | 6.142 |
| L (μH) | 0.030 | 0.770 | 0.115 | 0.613 |
| C (nF) | 0.683 | 0.653 | 1.065 | 1.829 |
| $p_0$ | 3.861 | 6.661 | 4.700 | 2.718 |
| $p_1$ | 5.775 | 5.068 | 5.147 | 3.923 |
| $q_0$ | 8.536 | 11. 61 | 14.51 | 8.360 |
| $q_1$ | 7.670 | 11.83 | 7.032 | 7.232 |
| $V_{ref0}$ (kV) | 8.113 | 8.519 | 9.106 | 11.61 |
| $V_{ref1}$ (kV) | 7.930 | 7.976 | 8.566 | 10.72 |

Table 4: CASE OF MODEL 4

| Parameter | [4] | [5] | [17] | [18] |
|---|---|---|---|---|
| R (Ω) | 0.604 | 0.528 | 0.703 | 0.157 |
| $L_0$ (μH) | 0.016 | 0.024 | 0.027 | 0.065 |
| $L_1$ (μH) | 0.067 | 0.205 | 0.130 | 0.403 |
| C (nF) | 0.860 | 1.197 | 1.388 | 1.117 |
| p | 3.051 | 5.174 | 4.628 | 3.865 |
| q | 8.047 | 7.536 | 7.216 | 10.03 |
| $V_{ref}$ (kV) | 7.058 | 7.282 | 6.895 | 8.06 |

## 6. RESPONSE TO FAST FRONT SURGES

The response of the various models implemented in ATP-EMTP to fast front surge 10kA, 1/2μs are shown in figures 9 to 12. These results show that all the models can reproduce the dynamic effects discussed before with a weak error.

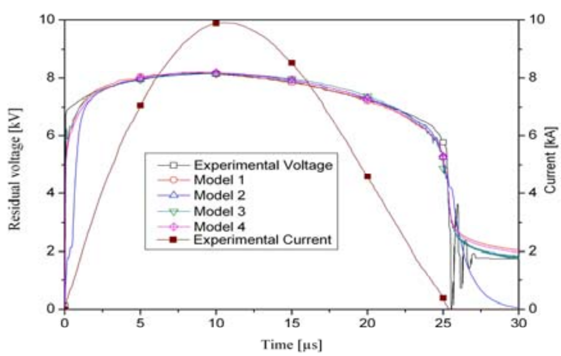


Figure 5. Comparison with the experimental residual stress of reference [4]

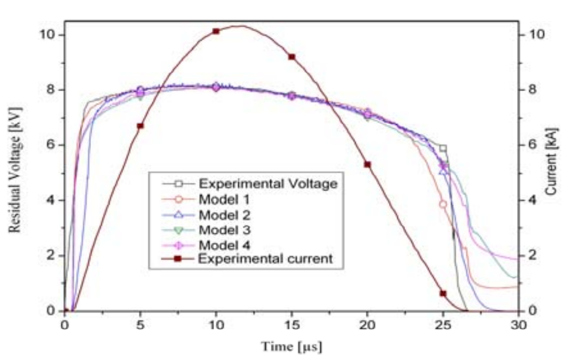


Figure 6. Comparison with the experimental residual stress of reference [5]

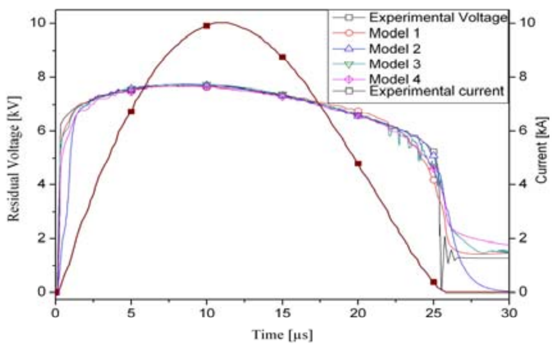


Figure 7. Comparison with the experimental residual stress of reference [17]

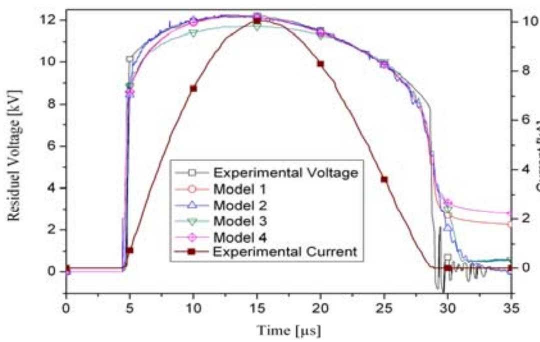


Figure 8. Comparison with the experimental residual stress of reference [187]

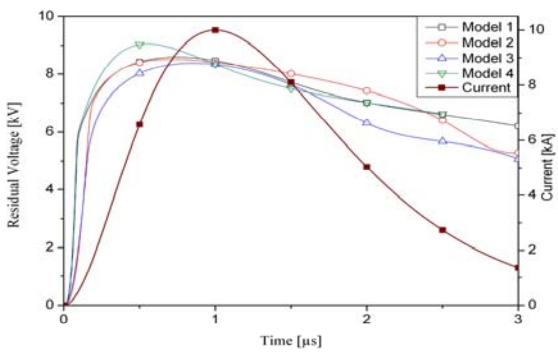


Figure 9. Response to 10kA, 1/2µs for the surge arresters of reference [4].

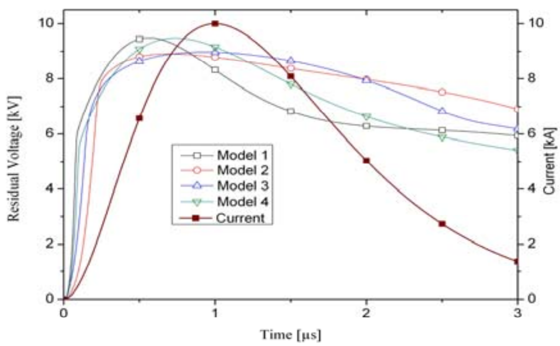


Figure 10. Response to 10kA, 1/2µs for the surge arresters of reference [5].

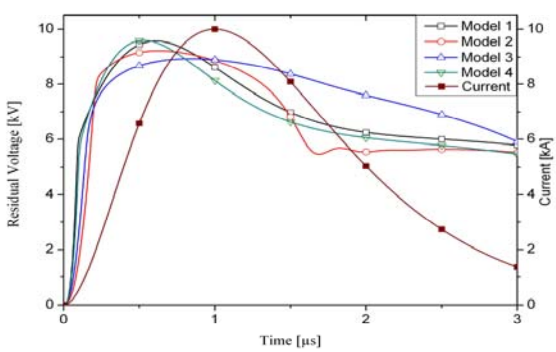


Figure 11. Response to 10kA, 1/2µs for the surge arresters of reference [17]

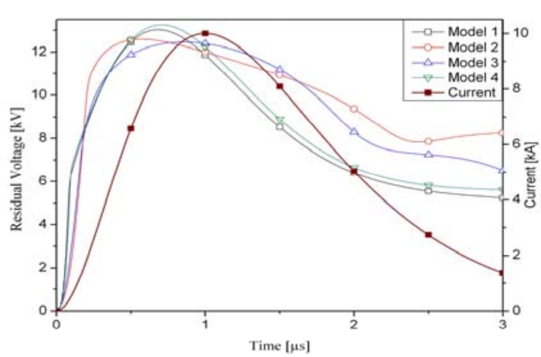


Figure 12. Response to 10kA, 1/2µs for the surge arresters of reference [18]

## 7. APPLICATION TO A TYPICAL EXAMPLE OF PROTECTION

Figure 13 shows a typical protection scheme by surge arresters. A lightning surge strikes at point 1. The current wave is divided into two parts; one part is propagated in the opposite direction of the line connected to the transformer. The reflection of this part must be avoided by considering that the line has infinite length. The other part is propagated towards the transformer. It is against this part that the surge arresters installed must protect the transformer.

The data of the various elements are as follows:

- distributed parameters line, Zc=350Ω and $V_p$=300m/µs;
- Rated voltage of the surge arrester ZnO is 189kV;
- The transformer capacitance is 3000pF.
- Surge wave: 10kA (1/2µs).

The surge arrester is installed at node 2. The impulse current is injected at node 1 and the voltages of the various nodes are recorded. The voltage at node 3 represents the voltage of the transformer. The results of simulation are shown in figure 14 by including the case where the surge arrester is represented by a simple non-linear resistance.

From this figure we can easily see that the predicted transformer voltage in the case of the use of the dynamic model (model 1 in this case) is more important than that predicted in the case of the use the static surge arrester model. That is in perfect agreement with the experimental data of the manufacturers.

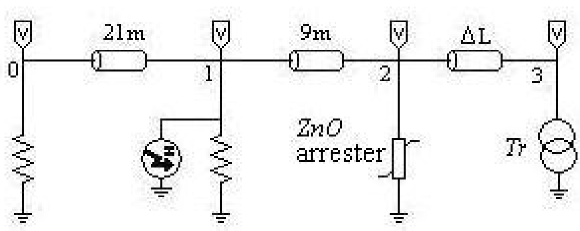


Figure 13. Typical protection scheme by surge arresters.

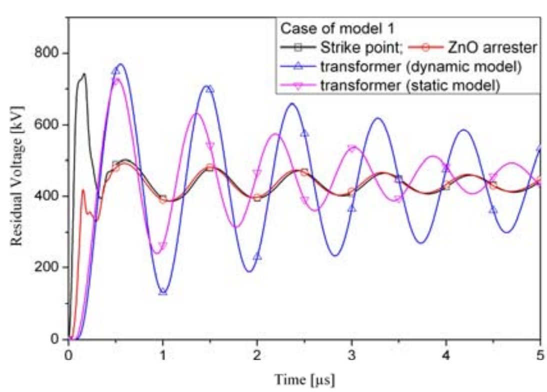


Figure 14. Test network node's voltages.

## 8. CONCLUSION

In this paper a new solution based on genetic algorithm method, to calculate the parameters of ZnO surge arresters models is proposed. The predicted results are compared with the experimental results available in the literature. The obtained results highlight well the efficiency of these algorithms in the identification of the parameters of ZnO surge arresters models. Moreover interfacing with ATP-EMTP makes calculation of the discharge voltage waveforms more flexible.

The use of a model in conjunction with the parameters optimized by GAs in a typical configuration of protection scheme by surge arresters is presented and discussed.

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