Neural Networks Approach of the Electric Arc in High Voltage Circuit Breakers

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Abstract: *The analytical models of electric arcs quenching in high voltage (HV) circuit breakers remains very difficult to formulate and requires hypotheses that are simplified exaggeratedly with regard to the reality. On the technical point of view, the application of neuron networks would be a no negligible supply for the simulation of electric arc quenching, enabling thus to be closer with the real properties of the breaker.*

The aim of this article is to introduce in a first time the neural networks in the mathematical modeling of the arc quenching in high voltage breakers, and then to present a comparative survey between the different training algorithms in order to enable to select the feed-forward propagation neural network and the back propagation algorithm the most adapted to simulation. This survey has been applied for a line breaker 245kV/50kA/50Hz, for which a default current of 90% of the breaking capacity has been applied.

Keywords*: Circuit breaker, Neural networks, Electric arc*

1. INTRODUCTION

The electric arc evolvement in a ionized medium at temperatures often overtaking 15000K [4, 5] makes that precise physical measurements are often very delicate, or else impossible to achieve, especially when taking in account the fact that the phenomenon evolves at impressive speeds [8]. Moreover, in spite of the important scientific work accumulated on electrical arcs quenching, as well in the theoretical than experimental domain, this physical phenomenon escapes to mathematical modeling that would enable to foresee its behavior with weak margin of uncertainty [4, 9].

In the same way, analytical model elaboration is still based on assumptions that are in most cases less justifiable physically. Therefore, neuron networks seem therefore capable to answer to our need for simulation, because they are able to provide a mathematical representation for non linear physical phenomena while basing on the reconstitution of an input-output relation from a set of ordinary functions and associated weights. Furthermore, a neural network doesn't need any theoretical model of the relation to be identified; it is sufficient to have some samples that can be generated experimentally. Dreyfus et al [2] show that neuron networks are used with success in phenomena of which the laws that govern them are unknown and for which one can achieve a large number of measurements.

In this paper, the problematic of analytical models development linked to electric arc cutting in high voltage circuit breakers will be presented. Afterwards, we will stain to conceive a neural network that models the breaking arc and to select the back propagation algorithm the best adapted to our survey. For this effect, we simulated a breaking process for a default current at 90% of the breaking capacity of an SF_6 high voltage line circuit breaker 245/50kA/50Hz.

A developed analytical model and experimental results allow a validation of the simulation especially by comparison with the works of P. Schavemaker et al [6] and J. L. Guardado [7] that studied experimentally the same breaker between 0 and 90µs.

2. CUTTING PRINCIPLE OF HV BREAKERS

In short circuit default conditions, the current to be cut can reach several tens or some hundreds of kilo Amperes [7-9]. And, thanks to the remarkable properties of the electric arc, the electromagnetic energy stocked in the inductive circuits can be dissipated. The arc that appears is constituted from a column of plasma composed by ions and electrons coming from the inter contact middle, or by metallic vapors issued from the breaker poles.

The zones of bridge anchorage on the contacts are at temperatures near of the temperature of metal fusion; thus, the thermo-ionic emission is possible. The melted bridges atmosphere is then a mixture of ionized gas and metallic vapors.

When the two poles are sufficiently separated, the melted bridges will be broken as a consequence of their submission to high thermal instabilities. These breakings evolve like explosions. Melted metal micro particles will be ejected with speeds ranging from 100 to 300 m/s, enabling so the ionization of the medium then the appearance of the electric arc [4]. The arc thus created will be maintained by the thermal energy that it liberates by joule effect, and it will be conductor so much that its temperature is sufficiently elevated.

One knows that the arc is initialized very quickly in the breaker but its behavior during the first milliseconds of its cutting is still less known in spite of the numerous accumulated works [4, 8-10].

3. ANALYTICAL MODELING OF THE ELECTRIC ARC

In the purpose of modeling the phenomena involved at the time of the breaker opening and, particularly, to study the arc voltage u evolvement, a new 0D model of arc quenching has been developed [1]. It was inspired from Cassie's thermal model [11] and implicates the thermal radiation emitted by the electric arc during its extinction. This model yields good results especially at the beginning of breaking.

We suppose then that the conductance of the arc is expressed solely as a function of the energy Q used for its formation: $g = g(Q)$ [8]. Thus, the total electric power provided to the arc by a current $i = 50.000\sqrt{2}\sin(314t)$can be written:

$$P = ui = P_p + \frac{dQ}{dt} + P_R \qquad (1)$$

P is the total power provided to the arc, P_p is the power lost by electrical conduction, P_R represents the power lost by thermal radiation and $\frac{dQ}{dt}$ is the necessary power to the arc creation.

We obtained then an equation that models the arc extinction at the opening of the poles of a high voltage breaker:

$$\frac{dg}{dt.g} = \frac{1}{\tau}\left(\frac{u^2}{{u_a}^2} - 1 - \frac{P_R}{P_P}\right)$$

In our survey, we set $f = \frac{P_R}{P_P}$ in order to be able to assess the contribution of the thermal power exchanged by radiation with regard to the power lost by electrical conduction. The equation that we obtained can be finally written as:

$$\frac{d\ln g}{dt} = \frac{1}{\tau}\left(\frac{u^2}{{u_a}^2} - 1 - f\right) \qquad (2)$$

For the numerical solving of equation (1), the Runge Kutta method was used under MATLAB environment. The initial conductance has been fixed to 10^4 S [6]. The constants τ and u_a are deducted from [6, 7].

4. NEURAL MODEL CONCEPTION

4.1. Data Presentation

The parameter that can best describe the extinction of electric arcs quenching is its voltage [8, 9]. Several authors performed measurements of the arc voltage at the opening of high voltage breakers [5, 7-10]. These authors first observed a sharp increase of the arc voltage at the contacts opening which corresponds to the arc initiation, after that, they measure relatively weak arc voltages with regard to the network voltage. Schavemaker et al [6] measure this arc voltage between 0 and 90µs at the opening of a breaker 245kV/50kA/50Hz for a default current at 90% of the breaking capacity. Its evolvement is presented on figure 1. Inputs and outputs of the neural model are respectively the values of time and arc voltage which values are taken from figure 1.

The input will be then represented by a vector $T = (t_i)$ of n components, where t_i is the ith temporal component and $1 \le i \le n$. The corresponding output vector will be noted $V(v_i)$, where v_i is the ith value of the arc voltage. These data will be grouped in a matrix under MATLAB environment.

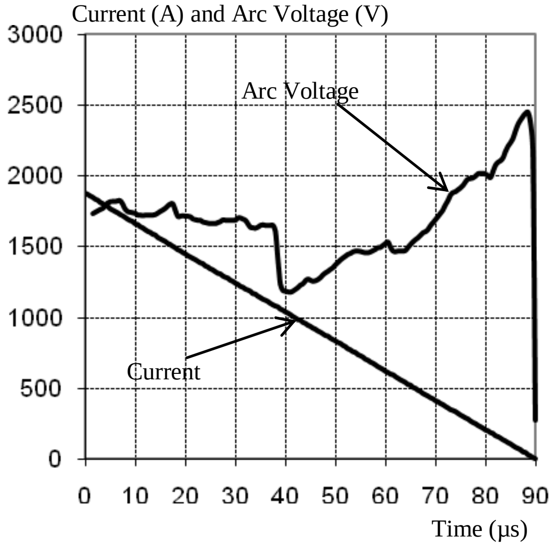

Fig.1.Current and arc voltage as a function of time [6].

The size of the database is obtained by an assessment of the neural network convergence. The executed tests led, in a first part, to a database stepped by 1, and in the second part, the length of the database is decreased while increasing the step by 5.

4.2. Training Phase

The training method used in this work is of back propagation type based on the algorithm of gradient decreasing. The training phase is executed with adjusting the weights by the back propagation algorithm until to have a fixed quadratic error between the wanted output and the neural network output [12]. For the different iterations, the back propagation algorithm provides the Mean Square Error performance function (MSE).

The weights initialization will be done by uncertainty manner. The back propagation algorithms that we used update the weights and the bias in the meaning to minimize the most rapidly the MSE. The training is considered complete after 1000 epochs (optimal number obtained by simulation) or when the maximal error on all output neurons, between the wanted value and the real value, is lower than 10^{-5}, for a given input of the training database.

4.3. Testing Phase

For the testing phase, we compared the values simulated by neural network to the experimental ones obtained by Schavemaker et al [6] for a period of extinction between 0 and 90µs. For that purpose, other data, different from those used during the training phase, are used.

4.4. Architecture of the Neural Network

The different tests done during the training phase led us to retain a forward propagation network (Under this configuration, all neurons of a given layer are usually joined to all neurons of the following layer) (figure 2). The newff command enabled, under MATLAB environment, to create this neural model.

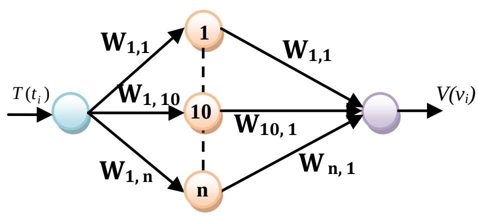

Fig.2. Architecture of the neural network

4.5. Structure of the Network

The network is constituted by three layers:

- The input one composed by only one neuron.
- A hidden layer with variable neurons number having a sigmoid type function of activation. The command "logsig" allows creating this function.
- An output layer with one neuron of which the activation function is linear positive and the command under Matlab is "poslin".

5. CHOICE OF THE BACKPROPAGATION

During the training phase, the connections weights are fixed initially by uncertainty way. A correction will be then done on these weights by the back propagation algorithm.

Since the wanted neural network outputs are known, we must therefore execute a supervised training [2, 3].

By reasons of the superabundance of algorithms and penury of methods enabling to compare and to well apply these algorithms, we only studied three algorithms of error back propagation:

- The resilient backpropagation ‘‘trainrp’’.
- The retro propagation with momentum (RPM) "traingdm'
- The Levenberg-Marquardt method (LM) "trainlm".

The use of an activation function of sigmoid type enables a non linear modeling of the arc breaking.

For each algorithm, a program under MATLAB was elaborated. It consists in a first time to forward propagating the inputs until obtaining an output calculated by the network. The second step of the program compares the calculated output to the real output with modifying then the weights so that at the next iteration, the error committed between these two outputs is minimized. The training will be considered finished after a number of 1000 epochs.

6. RESULTS OF SIMULATION

The evolvement of the performance of the neural network and the simulated voltage as a function of time was established for each type of algorithm. The same number of iterations (1000) is fixed for each simulation. This, concerns the two phases of the neural network: the training phase and the test phase.

Te training performance of the neural network with the lm algorithm (figure 3) reaches a performance value of 1.15302 10^{-8} at the end of 27 epochs. One can also notice that the error reaches 1.10503 10^{-9} for the gdm back propagation algorithm with momentum after 131 epochs (figure 5).

The neural model with these two algorithms provides a correct simulation. Figures 4 and 6 show a weak difference between simulation results and experimental measurements. The quenching simulation by the analytical model for a factor $f = 0.25$ presents arc voltages relatively closer to the experimental ones but only at the beginning of the breaking (figures 4, 6 and 8).

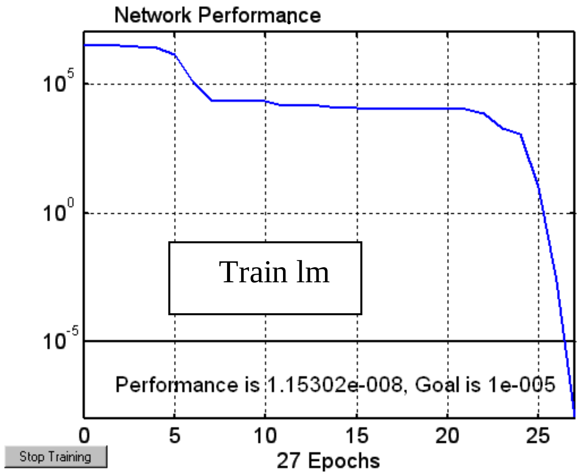

Fig.3. Performance of the network with lm algorithm (trainlm) after 27 epochs.

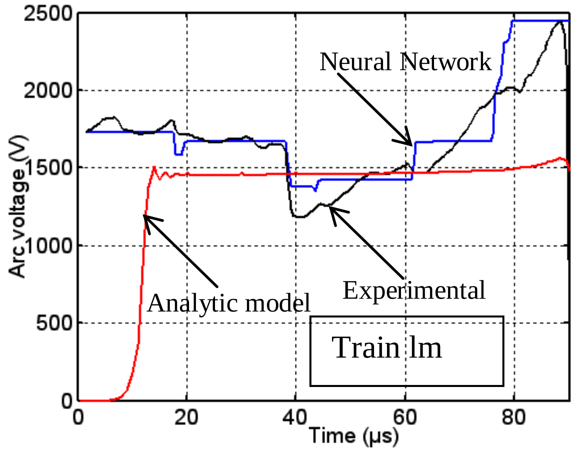

Fig.4 Arc voltage variations obtained with lm algorithm.

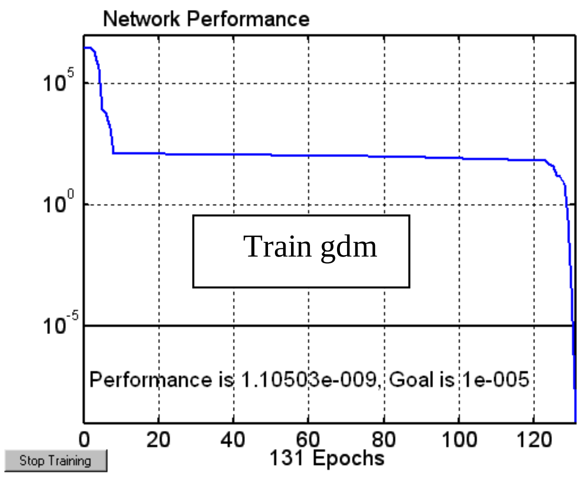

Fig.5. Performance of the network with the gdm algorithm (traingdm)

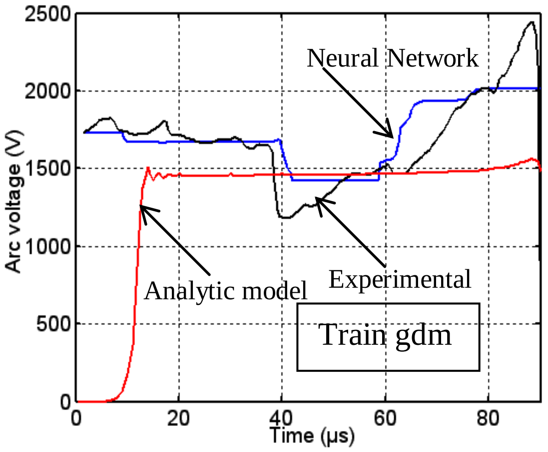

Fig.6. Arc Voltage variations obtained with the gdm algorithm

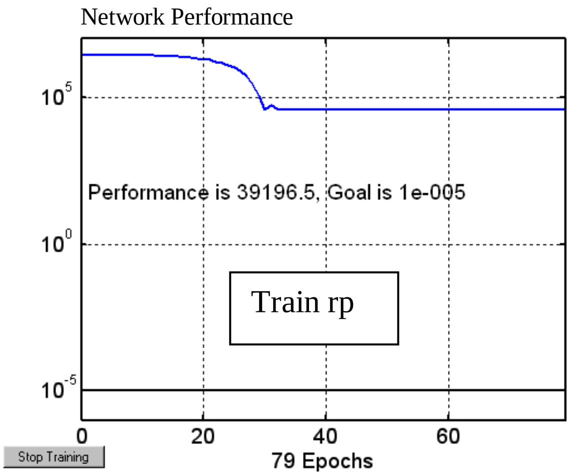

Fig.7. Performance of the network with the rp algorithmic (trainrp)

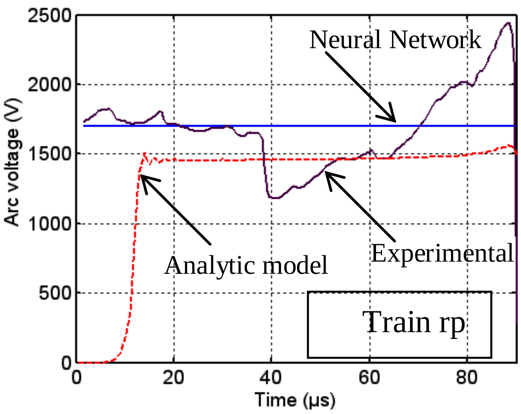

Fig.6. Arc Voltage variations obtained with the rp algorithm

7. CONCLUSION

In this paper, we presented a comparative survey of three training algorithms. The back propagation algorithms "lm" and with momentum "gdm" give the best performance for the arc quenching prediction in high voltage circuit breakers.

The simulation yields results close to the experimental ones. Nevertheless, this neural approach remains a real black tool that doesn't allow a fine interpretation of the physical phenomena responsible of the electric arc quenching. As a perspective of this work, it will be interesting to investigate other parameters linked to the breaking such as the plasma temperature and its pressure.

References

1. A. Ziani and H. Moulai, "Extinction properties of electric arcs in high voltage circuit breakers", Journal of Physics D: Applied Physics, Vol. 42, No 10, 2009, doi:10.1088/0022-3727/42/10/105205.
2. E. Davalo and P. Naim, "Des Réseaux de Neurones "Ed. Eyrolles, 1993.
3. B.Krose and P. Van der Smagt , "An introduction to neural network ", ebook of The University of Amesterdam, November 1996.
4. S. Vacquié, "Arc électrique", Technique de l'Ingénieur, Traité de Génie Electrique D 2870, 1995.
5. U. Habedank, "Application of a New Arc Model for the Evaluation of Short-circuit Breaking Tests", IEEE Trans. on Power Delivery, Vol. 8, No. 4, October 1993.
6. P. Schavemaker and L. Sluis, "An Improved Mayr-Type Arc Model Based on Current-Zero Measurements", *IEEE* Trans. Power Delivery, Vol. 15, N°2 , pp.580-584, 2000.
7. J. L. Guardado and S. G. Maximov, "An Improved Arc Model Before Current Zero Based on the Combined Mayr and Cassie Arc Models", IEEE Trans. Power Delivery, Vol. 20, N°1, January 2005.
8. S. Theoleyre, "Les techniques de coupure en MT", Collection technique Schneider Electric, N° 193, 1998.
9. A. Gleizes, J.J. Gonzalez and P. Freton, "Thermal plasma modelling", J. Phys. D: Appl. Phys, Vol.38, N°9, May 2005.
10. J.J. Gonzalez, F. Lago, p. Freton, M. Masquère and X. Franceries, "Numerical modelling of an electric arc and its interaction with the anode: part II", J. Phys. D: Appl. Phys,Vol. 38, No 2, pp. 306-318, January 2005,
11. A. M. Cassie, "Arc rupture and circuit severity, a new theory", *CIGRE*-Berlin, 1939.
12. M. Ben Hamed, L. Sbita and W. Abboud, " Neural Networks for controlled Speed Sensorless Direct Field Oriented Induction Motor Drives", JEE, Vol. 8, No.2, 2008.