Genetic algorithm approach to the modelling of polluted insulators

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Abstract: The phenomenon of flashover in polluted insulators has not yet been described accurately through a mathematical model. The main difficulty lies in the definition of the constants of the arc, which is formed in the dry bands when the voltage exceeds its critical value. The authors present a complex optimisation method based on genetic algorithms for the determination of the arc constants, using experimental results from artificially polluted insulators. First the well known model of Obenhaus for pollution flashover is used. This model results in a system of equations which cannot be solved with conventional arithmetic methods. The application of genetic algorithms enables the definition of the arc constants, resulting also in the calculation of the critical conditions at the beginning of the pollution flashover mechanism. In this way a mathematical model is established, which simulates accurately the experimental results.

1 Introduction

In recent years there has been a rapidly growing interest in the mechanism of development of the electrical arc in polluted insulators. Polluted insulators can cause, under certain circumstances, the development of electrical arcs which could have serious repercussions in the proper operation of networks. This phenomenon is called pollution flashover and is still not completely clear. A great number of projects have been carried out and many studies have been published all over the world concerning this phenomenon. In spite of these efforts it has become evident that there is no fully acceptable explanation of the pollution flashover mechanism, and therefore no general and efficient method of dealing with the problem.

The surface of the insulators is covered by airborne pollutants due to natural or industrial or even mixed pollution. As the surface becomes moist because of rain, fog or dew, the pollution layer becomes conductive because of the presence of ionic solids. A leakage current flows through the conducting surface film, generating heat which tends to increase the film temperature most rapidly at those points where the current density is greatest, i.e. at narrow sections of the insulator, such as the area around the pin. Eventually, the temperature in these areas approaches boiling point, and rapid evaporation of the moisture occurs producing dry areas. The development of the dry areas is independent of the insulator type, something that has also been verified experimentally, since the insulator's body diameter differs very little from one type to another.

The resistance of the dry zones is much higher than that of the wet areas. Consequently the voltage drop across the dry zones is higher and the line voltage is applied almost entirely on these zones. This causes the inception of primary arcs that can bridge the dry zones. If the combination of conductivity and electrical stress is sufficient to allow an arc to develop having sufficient current to make it self-sustaining under propagation, then flashover occurs.

Flashover modelling has been a topic of interest for many researchers [1–4]. A major problem in all those investigations is the definition [5, 6] of the value of the arc constants that affect the flashover process. Unfortunately the values of the constants determined from several investigations diverge substantially. This investigation targets the precise calculation of the arc value parameters, using relevant experimental results and close simulation of the insulator's behaviour under polluted conditions using a suitable mathematical model.

The experimental tests were carried out on artificially polluted insulators according to international standards. The thickness of the pollution film on the insulator surface was varied from low values to higher ones that correspond to heavily polluted industrial sites.

Among the measured parameters of the process is the critical value of the stress voltage one step before the flashover. The definition of the arc constants is performed using the measured values of the critical voltage for the flashover under several pollutant densities.

2 Modelling the flashover process

The flashover process on polluted insulators has been thoroughly investigated by several researchers. The simplest model that has been developed by Obenhaus [1] consists of a partial arc bridging the dry zone and the resistance of the polluted wet zone in series. Therefore, the voltage across the insulator will be

$$U = xAI^{-n} + (L - x)R_pI \qquad (1)$$

where xAI^{-n} is the stress in the arc and $(L{-}x)R_pI$ is the stress in the pollution layer. x is the length of the arc, L is the leakage path of the insulator, R_p is the resistance per unit length of the pollution layer, I is the leakage current and A and n are the arc constants.

The measurement of the resistance R_p of the wet zone is quite complicated. Therefore it may be substituted by the

IEE Proceedings online no. 20020343

DOI: 10.1049/ip-gtd:20020343

Paper first received 15th August 2000 and in revised form 8th February 2002

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conductivity σ_p of the pollution layer:

$$\sigma_p = \frac{1}{R_p} F_i \tag{2}$$

F_i is the form factor of the insulator that is given as follows:

$$F_i = \int_0^L \frac{1}{\pi D(l)} dl \tag{3}$$

where $D(l)$ is the diameter of the insulator that varies across the leakage path.

The critical condition for propagation of the discharge along the surface of the insulator to cause flashover is [7]

$$\frac{dI}{dx} > 0 \tag{4}$$

The voltage under this critical condition yields

$$U_c = x_c A I_c^{-n} + (L - x_c) K R_p I_c \tag{5}$$

Here the coefficient K was added to validate (1) at the critical instant of the flashover. Wilkins [4] introduced this coefficient in order to modify the resistance R_p of the pollution layer considering the current concentration at the arc foot point. A simplified formula for the calculation of K for cap-and-pin insulators is [8]

$$K = 1 + \frac{L}{2\pi F_i (L - x_c)} \ln \frac{L}{2\pi F_i \sqrt{\frac{I_c}{1.45\pi}}} \tag{6}$$

At the critical condition the length of the arc takes the value [4]:

$$x_c = \frac{1}{n+1} L \tag{7}$$

Further analysis [9] of the system equations at the moment of flashover yields for the critical current:

$$I_c = (\pi D_r \sigma_p A)^{1/(n+1)} \tag{8}$$

and for the critical voltage:

$$U_c = \frac{A}{n+1} (L + \pi D_r F_i K n) (\pi D_r \sigma_p A)^{-n/(n+1)} \tag{9}$$

where D_r is the diameter of the insulator

Eqn (9) provides the critical value of the voltage at the instant of flashover against the dimensions of the insulator (D_r and L), the arc constants A, n and the pollution σ_p, since F_i and K are also functions of the insulator's dimensions.

Obviously, the critical voltage can be calculated after the determination of the arc constants. These are the unknown parameters of the model.

3 Experiments

This paper uses experimental results on three different types of cap-and-pin insulator. The first two types have been tested by the authors in [9] and the third one by other investigators in [10]. The technical characteristics of these insulators are presented in Table 1.

The first type that was tested by the authors is a cap-and-pin suspension insulator and the second is a fog-type insulator. The tests on these two insulators were performed using the solid layer–cool fog method according to the international standards [11]. The surface conductivity of the pollution layer varies from 7.8 to 110.9 $\mu\Omega^{-1}$. The higher values correspond to industrial pollution in heavily polluted areas. The more important quantity in the experimental process is the critical voltage, i.e. the value of the supply voltage at the time just before the flashover.

The values of the critical voltage for all three insulators against the surface conductivity of the pollution layer are presented together with the computed results in Section 5.

4 Genetic algorithm

Genetic algorithms (GAs) are robust, stochastic and heuristic optimisation methods, based on biological reproduction processes. GAs are search algorithms based on the mechanics of natural selection and natural genetics: reproduction of an original population, performance of crossover and mutation, selection of the best. GAs combine the adaptive nature of natural genetics or the evolution procedures of organs with functional optimisations. An initial population is provided, which is represented by bit strings that evolve randomisation through successive generations in order to obtain an optimum for a particular fitness function.

In each generation, a new set of artificial strings is created using bits and pieces of the most suitable of the old ones. Solutions with high suitability are mated with other solutions by crossing over parts of solution strings. Strings may also mutate. Solutions with poor fitness are improved by crossover using highly fit solutions.

Artificial reproduction schemes were first developed in the 1970s [12] and were extended during the 1980s [13, 14]. The search area for the genetic algorithms is very wide and it usually converges to a point near the global optimum. Fine-tuning operations like hill climbing can be used to further refine the near-optimum solution. Simulating the survival of the most suitable among string structures, the optimal string (solution) is searched by randomised information exchange. Since a genetic algorithm utilises the coded discrete information of the artificial strings, it can be applied to ill-structured discrete optimisation as well as to continuous optimisation problems. Moreover, it searches a near-optimum point in a population of points.

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, the GA requires the initial set of points. This set is called the population, analogous to a biological system. It has a population size P_s. 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'.

Table 1: Dimensions of the investigated insulators

	Cap-and-pin 1	Fog-type	Cap-and-pin 2
Maximum diameter D_r	254 mm (10″)	254 mm (10″)	254 mm (10″)
Distance between centres	146 mm (5 3/4″)	146 mm (5 3/4″)	146 mm (5 3/4″)
Creepage distance L	305 mm (12″)	431 mm (17″)	279 mm (11″)
Form factor F_i	0.696	0.916	0.684

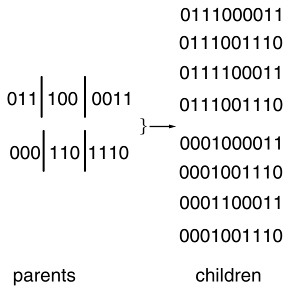

Fig. 1 *Possible combinations of crossover*

The next step is to form pairs of these points that will be considered as parents for reproduction, when they interchange N_p parts of their genetic material. This is achieved by crossover (Fig. 1). Crossover is used to create two new individual children from two existing individual parents picked from the current population. After the crossover there is a very small probability P_m of mutation. Mutation is the phenomenon where a random '0' becomes '1' or a '1' becomes '0'. Mutation is necessary because although reproduction and crossover efficiently search and mix existing strings, occasionally they may result in loss of some potentially useful 'genetic' material.

Assume that each pair of parents gives 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 now has $P_s + N_c P_s/2$ members. Then the process of natural selection is applied. According to this process only P_s members survive out of the $P_s + N_c P_s/2$ members. These P_s members are selected as the members with the higher values of F_g, if we attempt to achieve maximisation of F_g, or with the lower values of F_g, if we attempt to achieve minimisation of F_g.

Repeating the iterations of reproduction under crossover and mutation and natural selection, GAs can find the minimum (or maximum) of F_g. The best values of the population converge at this point. The termination criterion is fulfilled if either the mean value of F_g in the P_s-members population is no longer improved (maximised or minimised) or the number of iterations is greater than the maximum number of iterations N_{max}.

The experimental data U_c against σ_p and the geometrical characteristics D_r, L, F_i of the insulators of Table 1 are applied to (9), thus resulting in a set of 284 simultaneous equations with two unknowns, the arc constants A and n:

$$F_g = \sum_{i=1}^{284} |U_{c_i} - f_i(A, n)| \quad (10)$$

This set of equations must be minimised over A and n. This is why A and n are converted to the binary system and are considered as parts of a big chromosome. The search starts with a randomly generated population of such $2P_s$ chromosomes. Each constant (A, n) is converted to a t-bits binary number. $2t$ bits are required for the 'chromosome' of A, n with $0 < A < 500$, $0 < n < 1$. The available data in the international literature show that the values of constants A and n for thin pollution layers are in the range of 50–400 and 0.3–1, respectively ($A = 131.5$, $n = 0.374$ [9]; $A = 63.0$, $n = 0.76$ [3]; $A = 270$–461, $n = 0.42$–0.66 [6]).

By a random procedure, this population is split into pairs of parents that will be crossed, i.e. they will interchange their genetic material (with N_p parts for crossovers) always with a very small probability P_m of mutation. By this reproduction, a new population of $P_s + N_c P_s/2$ members will be formed, since each pair of parents gives birth to k children. The new population is filtered and only the P_s better members remain in the population. 'Better' means here the $2P_s$ lower values of $F_g(A, n)$. The others are erased. Repeating the iterations of reproduction, under crossover and mutation, and natural selection, GAs can find the minimum of $F_g(A, n)$, $0 < A < 500$, $0 < n < 1$, that is the point where the best values of the population converge.

The algorithm is summarised as follows:

- Step A: Find randomly the P_s initial t bits binary numbers.
- Step B: Convert the initial binary numbers to the initial population of P_s members.
- Step C: Increase the number of iterations.
- Step D: Select randomly the $P_s/2$ pairs from the population.
- Step E: From each pair of parents take k children by crossover. Each bit of each child has probability P_m for a mutation.
- Step F: Find the new population $P_s + N_c P_s/2$ (parents + children).
- Step G: From the new population select the P_s members with the lower values of F_g.
- Step H: If the number i of iterations is less than the maximum number N_{max} of iterations then go to Step C, else STOP.
- Stop.

5 Results

The application of the genetic algorithm starts with a randomly generated population of 20 chromosomes. It generates 20 random values for the arc constant A ($0 < A < 500$) and 20 random values for the arc constant n ($0 < n < 1$). Each constant, A or n, is converted to a 16-bit binary number. 32 bits are required for the chromosome. Each pair of parents with crossover generates four children. The crossover begins as each chromosome of any parent is divided into six parts, and the pair of parents interchange their genetic material. After crossover there is a 1% probability of mutation. The procedure is terminated after 500 generations. The above parameters of the algorithm are summarised in Table 2.

The application results in pairs of (A, n) values that finally converge to the optimum values $A = 124.8$, $n = 0.409$ as the number of iterations increases (Table 3). The whole procedure is shown in Fig. 2 where it becomes obvious that the algorithm converges rapidly to these values.

The next step is to verify the validity of the genetic algorithm by applying the computed values of the arc constants to the insulators of Table 1. Utilisation of the optimum values of the arc constants in the mathematical

Table 2: Parameters of the genetic algorithm

P_s	t	N_c	P_m	N_p	N_{max}
20	16	4	1 %	6	500

Table 3: Optimum value of the arc constants in each generation

Generation	1	20	40	60	80	100	120	140	150	200
A	120.707	122.259	124.239	124.288	124.802	124.738	124.818	124.802	124.802	124.802
N	0.4427	0.4188	0.4213	0.4152	0.4104	0.4104	0.4086	0.4091	0.4091	0.4091

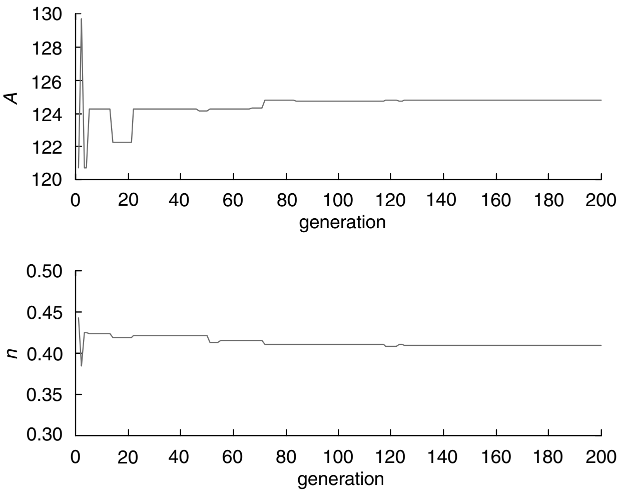

Fig. 2 *Convergence of the optimum values of the arc constants A and n in each generation*

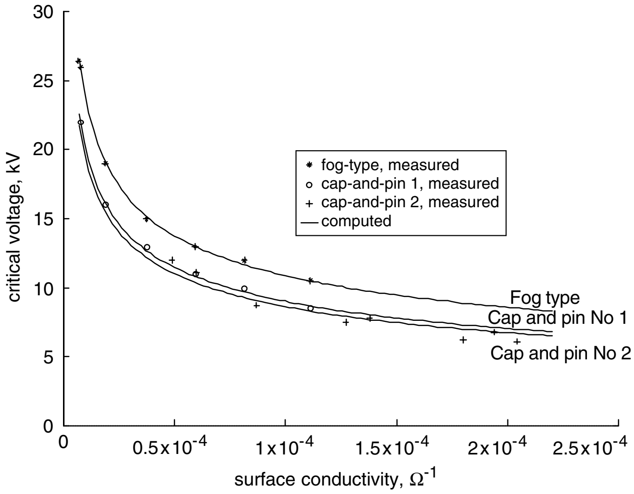

Fig. 3 *Critical voltage U_c against the surface conductivity σ_p*

model results in the critical voltage curves of Fig. 3. The Figure also shows the results from the experiments [9, 10]. The computed values agree well with the experiments.

6 Conclusions

One of the most important difficulties that researchers face nowadays, when using quite reliable mathematical models of polluted insulators' dielectric behaviour, is the definition of the arc parameters. The completely different values found in the literature are due to either the different experimental methodologies or to the complex mathematical solutions.

This study proposes a complex arithmetic optimisation method using genetic algorithms, which leads to more accurate results compared with those from conventional mathematical methods. Application of the model requires only the geometric characteristics of the insulator, the conductivity of the pollutant and the arc constants. Therefore, the determination of the arc constants permits the computation of the critical conditions for flashover. Experimental tests on several insulators show very good agreement between the measured values and the computed ones.

With this approach a new mathematical model has been developed. The model simulates the experimental results quite accurately and allows reliable applications. Moreover, comparison between widely approved simulation methods results in a better understanding of the transient phenomena in polluted insulators. In this way, it is hoped that the expensive and time-consuming experiments that are required for the investigation of the dielectric behaviour of polluted insulators and the insulation coordination of the electrical transmission lines may be minimised.

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