Peer-reviewed version available at *Energies* **2019**, *12*, 4110; doi:10.3390/en12214110

Article

Optimized Surge Arrester Allocation Based on Genetic Algorithm and ATP Simulation in Electric Distribution Systems

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Abstract: Lightning discharges in electric power networks generate voltage and current surges that are propagated through the electrical network causing damage and shutdowns in the electrical system. To protect the system against these phenomena, surge arresters are very effective and widely used by electrical utilities in their electric grids. This paper presents a methodology for optimized surge arrester allocation based on genetic algorithm (GA), creating a simulation environment in the software ATP (Alternative Transients Program) to implement the proposed methodology. The optimized allocation procedure is based on a fitness function that minimizes the cost of surge arresters and maximizes the number of protected equipment. To carry out this optimized arrester allocation procedure using ATP may demand too much processing time when running large distribution grids. To overcome this difficulty a procedure is proposed to obtain an overvoltage severity description of the grid and select the most critical electric nodes for the incidence of lightning discharges, in the GA allocation procedure. The case study is applied to the IEEE 123-bus electrical feeder to demonstrate the effectiveness of the proposed methodology.

Keywords: Transient Analysis; Surge Arrester Allocation; Genetic Algorithm; ATP

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1. Introduction

Lightning discharges and operational maneuvers, like switching of capacitor banks (CB), can generate overvoltage that propagates in the electrical network. The increased levels of voltage in distribution networks cause concern to electric power utilities, because the presence of overvoltage can cause, among others, malfunctioning and reduction of lifespan of equipment and devices, and in some cases might even cause permanent failures that may result in partial or complete shutdown of the electrical network. In addition to the losses due to equipment damage, if the electric power utility remains too long with no power supply, it shall be subjected to penalties which may reach significant values as the shutdown time period increases.

So, using mitigating measures is essential in order to avoid these costs, and as important as mitigation, it is to conduct preventive measures in order to protect the equipment and the electrical

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grid against overvoltage. One way to achieve equipment protection against high levels of overvoltage is through the installation of surge arresters along the power grid. A surge arrester, as long as it is properly grounded, is able to damp overvoltage, sending part of the electrical current to ground.

A recurring problem among electric utilities is how to define an efficient methodology to perform surge arresters allocation along the electric network. To perform this allocation in an efficient manner, it is recommended to take into consideration the optimal placement of surge arresters along the power grid. In addition to maintaining the quality of power delivered to consumers by keeping the voltage levels below the system insulation limit, it is of great importance to ensure the equipment protection and secure operation, as well as allow better planning on future equipment installation.

This article presents a methodology for surge arresters optimal allocation in electric networks based on genetic algorithm (GA). For each individual of the GA population the electric grid is automatically configured with a combination of surge arresters, which performances are evaluated through electromagnetic transient simulation using ATP.

Two main aspects differentiate this work with respect to others found in the literature. The first one is the use of a fitness function that takes into account weight factors to distinguish the desired protection level for electrical nodes and equipment individually, and also considering restrictions on the number of surge arresters to be allocated. This aims at maximizing the protection level and at the same time minimizing the number of surge arresters needed, which allows the user to configure the problem focus through the definition of the fitness function. The second aspect to be highlighted is the proposed procedure to select the most critical points in the electric network concerning the incidence of lightning discharges. This procedure makes possible to apply the optimal surge arrester allocation even in large electrical networks using ATP. Many works can be found in literature whose focus is the optimized allocation of surge arresters using metaheuristics and among them one can mention the following papers.

In [1] and [2] it was developed a computer application to determine the surge arresters optimal allocation in power systems minimizing the risk of failure, thus permitting the selection of appropriate protection schemes for each electrical network. As a consequence, protection costs are reduced in accordance to the costs of the elements actually protected, ensuring the continuity of service. It was used the software Matlab and its toolboxes Simulink and Powersys to simulate the electric networks.

In[1] the proposed procedure is based on statistical analysis of voltage surges and fuzzy logic techniques with the objective of establishing arresters locations that provide risks of failure at network nodes that are lower than the admissible limits. In [2] the proposed method is also based on statistical analysis of voltage surges but using Monte Carlo method and mathematical techniques to find the minimum risk of failure based on the gradient method. However, it can be only applied to single-phase electrical networks. In [2] the surge arresters allocation optimization is made by using a formulation based on genetic algorithms. The Monte Carlo method is used for estimating the electric distribution network lightning performance. The methodology is implemented in a software which links the YALUK-ATP and the genetic algorithm. The initial population is randomly generated, and the fitness function is set to minimize the percentile 60 or 90 of the probability distribution curve of the distribution network voltages.

In [3] the surge arresters allocation optimization is made by using a formulation based on genetic algorithms. The Monte Carlo method is used for estimating the electric distribution network lightning performance. The methodology is implemented in a software which links the YALUK-ATP and the genetic algorithm. The initial population is randomly generated, and the fitness function is set to minimize the percentile 60 or 90 of the probability distribution curve of the distribution network voltages.

In [4] the surge arrester allocation optimization is made based on genetic algorithm and network simulations with a developed electromagnetic transients program software. The fitness function is set to minimize overvoltage in a specific number of towers. Induced lightning discharges are used in the simulation studies.

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The method presented in [5] is based on genetic algorithms and an economic approach is taken into account by means of evaluating the cost of flashover insulation. Only indirect lightning is taken into account. The computer application was developed in MATLAB environment, and the simulation software to calculate the induced overvoltage is the ATP. After modeling the grid, ATP generates a plain file containing the grid data which are imported into MATLAB. So, each characteristic such as lightning and surge arresters parameters can be modified in the MATLAB environment. It is assumed that a flashover occurs when the maximum overvoltage is greater than 1.5 V_{CFO} (Critical Flashover Voltage). The initial population is randomly generated.

2. Proposed Metodology

To perform the surge arrester allocation using the proposed GA procedure, firstly it is necessary to model the electrical network via ATP input cards, which serve as template for the genetic algorithm. This template can be constructed manually by using ATPDraw module or automatically by using the procedure as presented in [6].

Once the template is built, it is necessary to choose in the electrical network under study, the critical electric nodes to apply lightning discharges, which will propagate voltage and current surges along the power grid [7]. It is important that all genetic individuals created in all populations of the GA evolution be tested in the same scenario, with the same lightning incidence points, otherwise it is considered that the GA individuals represent distinct scenarios. Before presenting the genetic algorithm configuration it is necessary to introduce some concepts that were used in the proposed methodology for surge arresters allocation.

2.1. Cross Mean Table

Firstly, it is highlighted that for every surge arrester allocation suggested by the GA solution, a simulation of ATP electromagnetic transient analysis is performed. With respect to this point, it is worth mentioning that the use of the GA in conjunction with ATP for the optimal solution is a process that consumes too much processing time, which makes it impracticable in terms of the solution time duration, the application of this optimization process to a great diversity of lightning discharges in large electric distribution grids.

Because of that, it was created the concept of Cross Mean Table (CMT) which represents an organized summary of ATP simulation results obtained by simulating the incidence of lightning discharge in each electrical node of the grid, one by a time. In this case, when applying the GA optimization procedure, instead of considering lighting discharges in all nodes of the electric network, only the electrical nodes with the most critical over voltages values obtained in the ATP simulation are considered for incidence of lightning discharges and participate in all GA generations.

To construct the CMT it is necessary to create a $(m+1) \times n$ array, as depicted in Figure 1, where m is the total number of nodes in the electric network and n is the number of nodes at which it is desired to evaluate the impacts of lightning discharges, such that $m \leq n$. For each node n in the column array it is simulated, by using ATP, the incidence of a lightning discharge with same parameters for each node. The highest overvoltage resulting in phases A-B-C of nodes m due to lightning discharges in nodes n are stored in the column array forming the elements $CMT(i, j)$, for $i = 1, 2, \ldots, m$.

	Node 1	*Node 2*	*Node 3*	…	*Node n*
Node 1	V_{11}	V_{12}	V_{13}	…	V_{1n}
Node 2	V_{21}	V_{22}	V_{23}	…	V_{2n}
Node 3	V_{31}	V_{32}	V_{33}	…	V_{3n}
…	…	…	…	…	…
Node m	V_{m1}	V_{m2}	V_{m3}	…	V_{mn}
V_{avg}	$V_{avg(1)}$	$V_{avg(2)}$	$V_{avg(3)}$	…	$V_{avg(n)}$

Figure 1. Cross Mean Table.

A sensitivity analysis is performed in order to evaluate for which node j, the overvoltage caused in the electric network is more critical. The average of overvoltage per column is calculated and stored in the array V_{avg}. Once this array is sorted, it is possible to identify the most critical nodes for lightning discharge. So, it is reasonable that any study done to mitigate the impacts caused in the network due to lightning discharges should first consider the most critical nodes, assuming that by minimizing damages caused in this scenario, shall consequently reduce impacts due to lightning discharges in other nodes.

2.2. Genetic Algorithm

Genetic algorithm is a technique of local search that uses evolution-based procedures to make small changes in a population of chromosomes in searching for an optimal solution [8]. In the following it is presented a discussion on the main elements that compose the genetic algorithm fundamentals applying to the problem of surge arrester optimal allocation.

2.2.1. Chromossome

The chromosome represents a solution to be tested as a possible candidate to the optimal solution for the problem. In Figure 2 it is represented the chromosome definition to be used in the problem of surge arresters optimal allocation as proposed in this paper, where each gene represents a network electric node that is candidate to receive a set of surge arrester.

Node 1	*Node 2*	*Node 3*	*Node 4*	…	*Node n*
0.2345	0.5001	0.8903	0.4590	…	0.5000

Figure 2. Example of chromossome.

The number of chromosome genes is equal to the number of electrical nodes that a study is desired and do not have any surge arrester installed. Each gene uses real coding with values in the range of [0, 1].

2.2.2. Individual

The population individuals, as presented in Figure 3, refer to solutions found from decoding a chromosome. Each gene is decoded considering the value 0.5 as cutoff point, that is, if $gene \leq 0.5$ then it is assigned a value 0, otherwise it is assigned a value 1. A gene with value 0 indicates that the corresponding electric node has no surge arresters allocated; value 1 indicates that surge arresters are allocated in all phases of the corresponding node, being one, two or three-phase nodes.

Node 1	*Node 2*	*Node 3*	*Node 4*	…	*Node n*
0	1	1	0	…	0

Figure 3. Example of individual.

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2.2.3. Population

Population is a set of chromosomes that will undergo changes over the genetic algorithm generations. Two population settings have been defined that can be chosen by user. The first configuration is set to carry out a search for a solution that performs optimal allocation with the least amount of surge arresters possible. For this, the minimum population size is defined as being twice the sum of the number of candidate electric nodes plus 1 as in (1).

$$size = 2 \times (n + 1) \tag{1}$$

Half of this population is stochastically generated using a uniform distribution to generate the genes, and the other half in a deterministic way, where one of the chromosomes created does not contain surge arresters allocated, that is, all genes are equal to zero. The other chromosomes have only one surge arrester set allocated. In other words, for each candidate electrical node, a chromosome with only one surge arrester set is placed in the corresponding gene, and no surge arresters in the other genes, according to Figure 4.

Node 1	*Node 2*	*Node 3*	*Node 4*	...	*Node n*
0	0	0	0	...	0
0	0	0	0	...	1
0	0	0	0	...	0
0	0	0	1	...	0
0	0	1	0	...	0
0	1	0	0	...	0
1	0	0	0	...	0

Figure 4. Population configuration 1.

If the electrical network has many electrical nodes and equipment, the combined execution time of GA and ATP may take several hours, depending on the number of generations and the number of distinct chromosomes that are created over the generations. As a result, the second configuration aims to reduce the number of chromosomes to be generated in order to reduce execution time. This way it is suggested to focus the search around the electric nodes whose lightning discharges have caused the most critical over voltages, according to the results obtained from the *Cross Mean Table* analysis.

Like the in the first configuration, in the second one, half of the population is also generated stochastically using a uniform distribution to generate the genes, and another half deterministically. The difference is in the size of the population and how individuals are created. The population size is defined as in (2), where n is the number of lightning discharges to be analyzed.

$$size = 2^{n+1} \tag{2}$$

The deterministic half consists of generating the truth table of surge arresters combinations in the electric nodes where there was incidence of lightning discharges. Figure 5 presents an example of the deterministic construction, where each individual represents one of the 2^n possible combinations, considering the number of discharges $n = 3$, for illustrative purpose. In these individuals, surge arresters will be allocated in the n electric nodes with value 1, and in the others it is assigned value zero, that is, no surge arrester allocated.

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	Node Discharge 1		Node Discharge 2		Node Discharge 3	
...	0	...	0	...	0	...
...	0	...	0	...	1	...
...	0	...	1	...	0	...
...	0	...	1	...	1	...
...	1	...	0	...	0	...
...	1	...	0	...	1	...
...	1	...	1	...	0	...
...	1	...	1	...	1	...

Figure 5. Population configuration 2.

2.2.4. Selection

The tournament selection operator is used, where a set of chromosomes is randomly chosen to participate in a *ring*. The two best evaluated chromosomes are chosen as parents to generate a new pair of chromosomes. The size of the *ring* is defined by the user.

2.2.5. Crossover

The crossover operator used is the arithmetic crossover. With each generation a new empty population is created and filled with new individuals until it reaches the configured size. For that, repeatedly two chromosomes are selected and a random number is generated using a uniform distribution. If it is verified that this number satisfies the stipulated crossover rate, a random number α is generated which will serve to create weights by performing the weighted average of the parent chromosomes genes, generating new genes for each child chromosome, as in (3) and (4). Otherwise, two new chromosomes with the same parent genes are generated.

$$child1[i] = \alpha \times parent1[i] + (1 - \alpha) \times parent2[i] \tag{3}$$

$$child2[i] = (1 - \alpha) \times parent1[i] + \alpha \times parent2[i] \tag{4}$$

2.2.6. Mutation

The mutation operator used is the reflexive gaussian mutation. For each chromosome gene a random number is generated using a uniform distribution and checked if it satisfies the configured mutation rate. If false, the gene remains unchanged; otherwise a number is generated from a gaussian distribution with mean $\mu = 0$ and standard deviation σ in the range of [0, 1] as defined in the settings.

The standard deviation represents the maximum change that the gene will suffer. The number generated in the range $[-\sigma, \sigma]$ is added to the gene, if the result exceeds the range limits of [0, 1], the surplus is reflected in the opposite direction, so the gene will never overcome this range.

2.2.7. Fitness

The fitness function aims to evaluate how good the solution represented by a chromosome is. To perform this evaluation it is necessary to execute the ATP input cards using the *template* created and modified based on the individuals, allocating a surge arrester set at the electric nodes where there is a gene with value 1. For each individual, n lightning discharge scenarios are simulated. At the end of each simulation the maximum phase voltage peaks of each electrical node is extracted from the output file.

The defined fitness function is composed of the sum of 3 terms. The first term B aims to maximize the number of electrical nodes that are within the V_{CFO} voltage limit, which varies according to the feeder nominal voltage $(V_{nominal})$ and represents the voltage level above which the flashover occurs and, consequently, shutdown. For that, the percentage of electrical nodes whose electrical voltages are less than V_{CFO} is calculated according to (5).

$$B = \frac{B_{total} - B_{over}}{B_{total}} \times 100 \tag{5}$$

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Where,

B_{total} is the total number of electrical nodes in the electrical network.

B_{over} is the total number of electrical nodes that has exceeded the electric voltage limit of V_{CFO}, considering V_{CFO} equal to the NIL (Basic Isolation Level).

An electrical node violates the V_{CFO} limit when at least one of its phases presents a voltage level greater than V_{CFO}, defined as in Table 1, adapted from NBR 6939 [9]. When a nominal voltage occurs at the ends of each range, a more conservative profile is adopted using the lowest value of V_{CFO} among the possible ones.

Table 1. Insulation voltage levels: V_{CFO} limits

$V_{nominal}(kV)$			$V_{CFO}(kV)$
	$x \leq$	3.6	20
3.6	$\leq x \leq$	7.2	40
7.2	$\leq x \leq$	12	60
12	$\leq x \leq$	15	95
15	$\leq x \leq$	24	125
24	$\leq x \leq$	36	145
36	$\leq x \leq$	72.5	325
72.5	$\leq x \leq$	92.4	380
92.4	$\leq x \leq$	145	450
145	$\leq x \leq$	245	650

The second term E consists of evaluating the percentage of equipment that has been protected according to (6). A protected equipment is one whose electrical node has electric voltage level within the V_{CFO} limit in all its phases. Capacitor banks (BCs) and transformers are considered as equipment.

$$E = \frac{E_{total} - E_{over}}{E_{total}} \times 100 \tag{6}$$

Where,

E_{total} is the total number of equipment in the electrical network.

E_{over} is the total number of equipment that is connected at electric nodes that have exceeded the V_{CFO} limit.

The third term A evaluates the number of surge arresters that were required to perform the optimal allocation, as in (7), considering that each electrical node receives a surge arrester in each phase. This term acts as a bonus if $A_{allocated} \leq A_{desired}$; otherwise, it acts as a penalty to the individuals that have exceeded the established *desired* number of surge arrester.

$$A = \frac{A_{desired} - A_{allocated}}{A_{max} - A_{desired}} \times 100 \tag{7}$$

Where,

A_{max} is the maximum number of surge arresters that can be allocated in the electrical network, that is, a surge arrester in each phase of each electric node.

$A_{desired}$ is the user-defined desired number of arresters to be allocated.

$A_{Allocated}$ is the amount of allocated surge arresters by the GA procedure.

The final fitness function is defined by (8), as the weighted sum of terms B, E and A, where F_{ep} is the equipment protection factor and F_a is the surge arrester factor, both of which can assume values in the interval [0, 1]. It is possible that the weighted sum in (8) generates a negative value, and in this case the fitness value will be set to zero, through the *max* function that returns the largest between two numbers.

$$fitness = max(0, (1 - F_{ep}) \times B + F_{ep} \times E + F_a \times A) \tag{8}$$

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However, the user must define a *limit* number of surge arresters (A_{limit}) that can be tested on each solution. Individuals who exceed A_{limit} will not be simulated by the ATP and their fitness will be zero. In summary, individuals will recieve in ther fitness, a bonus if $A_{allocated} \leq A_{desired}$ or a penalty if $A_{desired} < A_{allocated} \leq A_{limit}$, and in the case $A_{allocated} > A_{limit}$ they will not be simulated in ATP.

2.3. Memory Map

A simulation run in ATP may take a few minutes depending on the size of the electrical network and the simulation parameters. It is necessary to perform an ATP simulation for each individual that was generated by the GA evolution, but it is possible that the same individual be generated more than one time during the GA execution.

Regardless of how many times the same simulation is performed the result obtained is the same. Therefore, these extra ATP calls spend unnecessary processing time, and to avoid them a memory map is used to store the calculated fitness.

A memory map is a data structure that indexes a value to a unique key, which is used as the search parameter. In Python a memory map is implemented in dictionary form. For this application the key consists of a tuple of the individual genes and the value is the calculated fitness and the tiebreaker criteria, as in Figure 6. The main advantage of using this feature is the reduced processing time, however there is also an increase in memory consumption.

key	:	*value*
(0,0,0,0,0)	:	*[fitness $_0$, E_0, A_0, B_0]*
(0,0,0,0,1)	:	*[fitness $_1$, E_1, A_1, B_1]*
(0,0,0,1,0)	:	*[fitness $_2$, E_2, A_2, B_2]*
(0,0,0,1,1)	:	*[fitness $_3$, E_3, A_3, B_3]*
...	:	...
(1,1,1,1,1)	:	*[fitness $_{31}$, E_{31}, A_{31}, B_{31}]*

Figure 6. Example of memory map.

2.4. Parallelization

Running the genetic algorithm sequentially can be very costly due to the time spent with each ATP simulation. Therefore, it is essential to perform parallelization to perform multiple simulations of ATP simultaneously. Parallelization was performed in processing the fitness function and in the methodology of constructing the CMT because both routines use exhaustive ATP executions.

3. Results Discussions

To test the proposed methodology, the IEEE-123 Node Test Feeder [10] is used, whose single-line diagram can be seen in Figure 7. To guarantee the electrical network has no islands and is radial, all switches were considered closed except switches 18-135 and 54-94.

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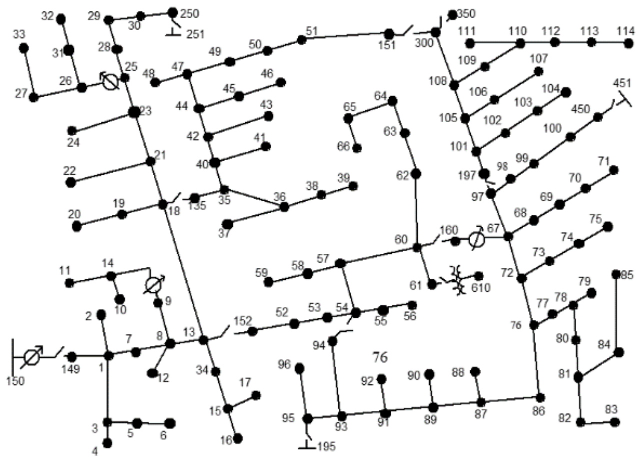

Figure 7. IEEE 123 node eletric test feeder sigle-line diagram.

Figure 8 represents the sorted array V_{avg} obtained from the CMT, considering a lightning discharge of 10 kA. The runtime spent to get this curve was 6.12 minutes. As can be observed the three most critical nodes analyzed are B_{135}, B_{35} and B_{40} presenting overvoltage above 2 MV. From the definition of these nodes, the GA execution will be done considering the incidence of lightning discharges only in the three most critical nodes, firstly the most critical (B_{135}), then the two more critical (B_{135} and B_{35}) and finally the three more critical (B_{135}, B_{35} and B_{40}).

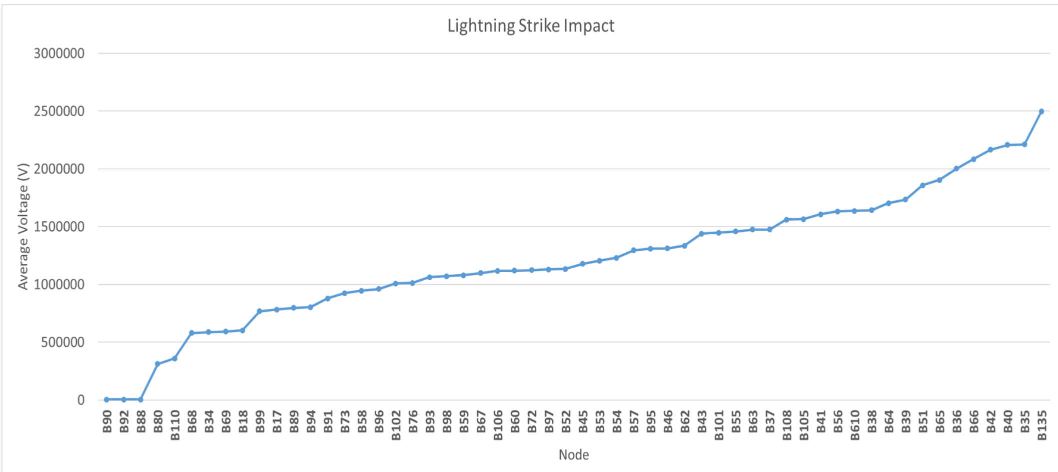

Figure 8. Graphical representation of CMT results for lightning discharges of 10 kA in each electric node of IEEE-123 node test system.

The GA parameters setting is described in Table 2. The minimum population size used was defined by (2).

Table 2. Genetic algorithm configuration.

Generations	Population Size	Ring Size	Crossover Rate (%)	Mutation Rate (%)	σ
30	16	3	80	50	0.5

The GA was executed considering six different configurations of fitness settings, as presented in Table 3. Each configuration has a specific focus that can vary between the high priority protection of electrical nodes with already installed equipment, namely transformers and capacitor banks, or an equal priority protection scheme of all electrical nodes, considering or not a restriction on the maximum

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number of surge arresters to be allocated. For the current case study, the tests were performed with $A_{desired} = 29$ and $A_{limit} = 58$.

Table 3. Fitness configuration.

Configuration	F_{ep}	F_a	Description
1	0	0	Equal priority protection of all nodes, without limitation of surge arresters.
2	0	1	Equal priority protection of all nodes, with limitation of surge arresters.
3	1	0	Priority protection for transformers and CBs, without limitation of surge arresters.
4	1	1	Priority protection for transformers and CBs, with limitation of surge arresters.
5	0.5	0	Equal priority protection of all nodes, transformers and CBs, without limitation of surge arresters.
6	0.5	1	Equal priority protection of all nodes, transformers and CBs, with limitation of surge arresters.

As can be seen by inspection of Tables 4, 5, and 6, all configurations have presented a good percentage of equipment protection in all cases. For a lightning discharge at the most critical electric node B_{135}, the best surge arrester allocation solution was obtained by configuration 6, which resulted in 100% protection of equipment and 98.89% protection of electric nodes in general, allocating the smallest number of surge arresters. In the case of lightning discharges at nodes B_{135} and B_{35}, configurations 5 and 6 presented similar results for equipment protection reaching 89.23%, and allocating 56 and 55 surge arresters respectively. For lightning discharges at nodes B_{135}, B_{35}, and B_{40} the best solution corresponds to configuration 3, which reached 92.31% of equipment protection, allocating 58 surge arresters, that is the allowed limit.

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Table 4. Results obtained when simulating a 10 kA lightning discharge at bus B_{35}.

Configuration	Fitness (%)	B (%)	E (%)	$A_{allocated}$	AG runtime (min)
1	94.44	94.44	95.38	50	17.15
2	76.05	91.11	90.77	54	13.71
3	98.46	97.78	98.46	55	16.06
4	80.93	94.44	95.38	53	8.01
5	99.44	98.89	100.00	54	16.93
6	**87.40**	**98.89**	**100.00**	**49**	**21.44**

Table 5. Results obtained when simulating a 10 kA lightning discharge at buses B_{35} and B_{42}.

Configuration	Fitness (%)	B (%)	E (%)	$A_{allocated}$	AG runtime (min)
1	86.67	86.67	86.15	56	22.70
2	70.96	80.00	78.46	44	46.93
3	76.92	75.56	76.92	53	26.16
4	77.72	86.67	86.15	43	64.38
5	89.06	88.89	89.23	56	23.21
6	**73.40**	**88.89**	**89.23**	**55**	**34.54**

Table 6. Results obtained when simulating a 10 kA lightning discharge at buses B_{35}, B_{42} and B_{36}.

Configuration	Fitness (%)	B (%)	E (%)	$A_{allocated}$	AG runtime (min)
1	81.11	81.11	80.00	57	47.13
2	77.95	90.00	90.77	49	95.88
3	92.31	91.11	92.31	58	83.26
4	72.63	87.78	87.69	54	102.24
5	83.21	83.33	83.08	58	63.29
6	**68.12**	**80.00**	**81.54**	**50**	**83.87**

The GA average runtime for Tables 4, 5 and 4 were 15.55 min, 36.32 min and 79.28 min respectively. The larger the number of critical nodes to be analyzed the higher the runtime due to the increased ATP executions. A linear approximation, for example, considering that all IEEE-123-grid electric nodes are to be analyzed it would spend approximately 54 hours of continuous computing processing. Typical electric distribution grids may have thousands of electric nodes, so the direct application of GA optimization procedures using ATP may become not viable with respect to processing time, and using a procedure like the one proposed in this article may become it viable.

The GA convergence performance for configurations 1-6 has exhibited similar profiles. Configuration 1 was selected to illustrate this performance, whose results can be seen in Figures 9, 10 and 11 respectively. For each GA execution Figure 9 presents the fitness function convergence profile, being the best individual convergence presented in dotted blue line and the population convergence in dotted red line, with the respective standard deviation confidence interval.

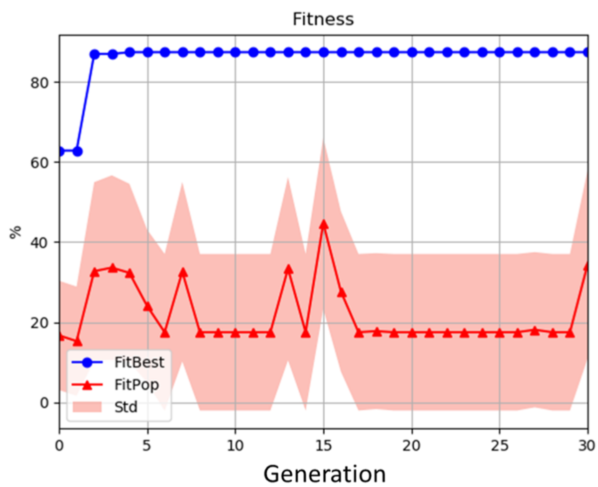

Figure 9. Fitness convergence.

The percentage of protected equipment and allocated surge arresters are updated with each generation, trying to keep the amount of protected equipment as bigger as possible, and the number of arresters as smaller as possible, as depicted in Figures 10 and 11.

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In Figure 10 it is highlighted in dotted blue line the percentage of equipment protection for the best individual presented in Figure 9. It is also presented in dotted red line the population curve representing the average of all individuals in the generation, which variation profile is constrained by the standard deviation confidence interval.

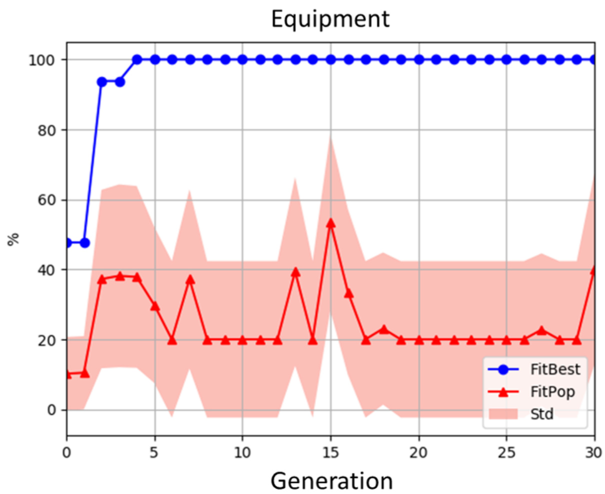

Figure 10. Protected equipment.

Figure 11 presents in dotted blue line the amount of allocated surge arresters for the best individual for each GA generation and the corresponding allocation profile for the average population individuals in dotted red line.

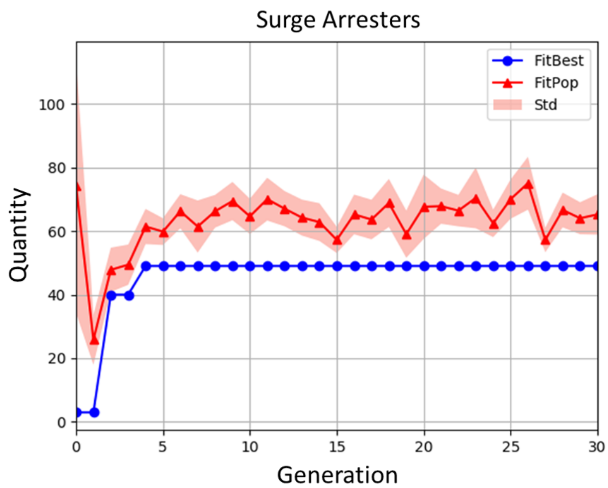

Figure 11. Allocated surge arresters.

To evaluate the GA optimal solutions performances in terms of the resulting system overvoltages, the Cross Mean Table methodology is again applied, considering 10 kA lightning discharges in all electric nodes, but now considering the optimal allocation of surge arresters as obtained by the GA optimal solutions. In order to exemplify this performance, configuration 6 as presented in Tables 4, 5 and 4 will be used. Figure 12 shows the CMT results obtained after the optimal allocation of surge arresters, when considered the most critical node (dotted orange curve), the two most critical nodes (gray dotted curve) and, finally, the three most critical nodes (yellow dotted curve) . These results are compared with results obtained for the original system without surge arrester allocation (dotted blue curve), as presented in Figure 8.

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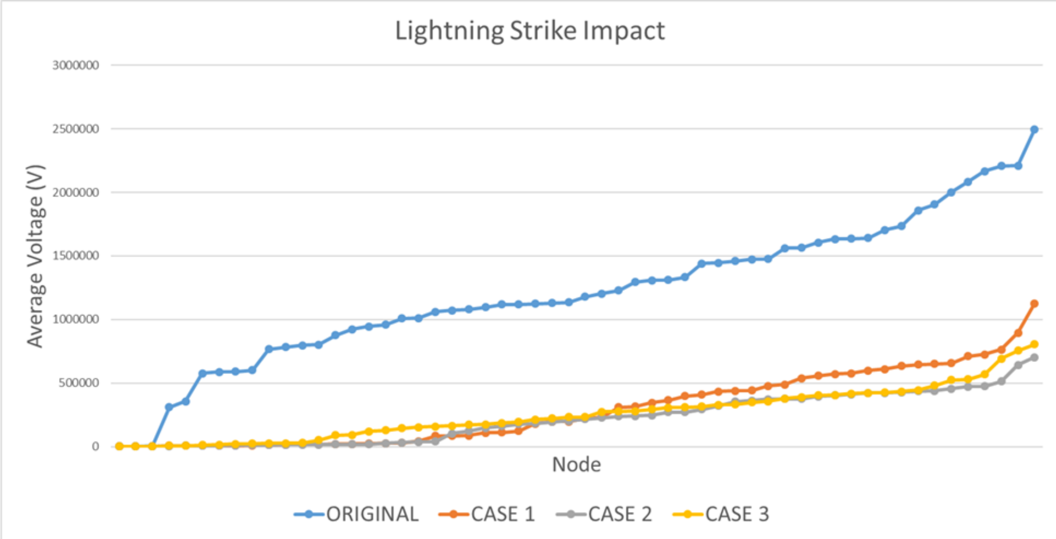

Figure 12. Graphical representation of CMT results before and after surge arresters allocation.

It is observed in Figure 12 that in all cases considered, that is, only the most critical node, the two most critical nodes, and the three most critical nodes, the proposed methodology presented a significant reduction of overvoltage with respect to the condition without surge arresters allocation (original electric network). The comparison among the three cases of optimal allocation, either observing Figure 8, or the previous results presented in Tables 4, 5 and 4, demonstrates that they are very similar, with slight variations between the solutions presented. In this way one has a varied set of feasible solutions to be adopted. It is worth to emphasize that by using the proposed methodology, these solutions are obtained with a reduced computational effort, when compared with standard optimization procedures using GA.

4. Conclusions

It is well known by researchers and engineers of electrical systems that using ATP as a calculation tool in optimization procedures, such as those using genetic algorithms, demands a lot of processing time, which can even make the combined use of AG and ATP unfeasible for the solution of optimization problems in large electric networks. This was one of the main aspects covered in this article, being proposed an optimization procedure to overcome this difficulty which is based on the analysis of the electric network regarding the critical over voltages caused by atmospheric discharges. The proposed solution using the CMT description of the electric network demonstrated to be very effective as a starting condition of the GA optimization procedure.

Surge arresters optimal allocation based on the most critical over voltages analysis proved to be quite effective, obtaining very good results regarding the over voltages reduction at all electric nodes, ensuring high percentages of electric nodes below the flashover voltage limit.

It is worth mentioning, too, that the proposed fitness function allows important features of electrical systems operation to be met in planning surge arresters allocation in electrical networks, namely, to protect a maximum possible number of electric nodes and equipment, with the least possible financial investments in surge arresters acquisition. The results demonstrated the proposed methodology has a great potential for application in real problems of electric distribution utilities, which typically involve large electric networks, serving as a guide in decision making concerning surge arresters allocation planning.

Author Contributions: Conceptualization, G.V.S.R., R.P.S.B, J.R.S.M. and U.H.B; methodology, G.V.S.R., R.P.S.B, J.R.S.M. and U.H.B; software, G.V.S.R., J.R.S.M., I.M.A., D.S.A.C and A.C.S.; validation, G.V.S.R. and U.H.B; formal analysis, G.V.S.R., R.P.S.B, J.R.S.M. and U.H.B; investigation, G.V.S.R., R.P.S.B, R.M and J.S.S.; resources, G.V.S.R.,

Peer-reviewed version available at *Energies* **2019**, *12*, 4110; doi:10.3390/en12214110

R.P.S.B, J.R.S.M. and J.S.S.; data curation, G.V.S.R.; writing–original draft preparation, G.V.S.R.; writing–review and editing, U.H.B; visualization, G.V.S.R.; supervision, J.S.S.; project administration, M.V.A.N

Funding: This research was funded by in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001. This research was also funded in part by Centrais Elétricas do Pará (CELPA) and the Companhia Energética do Maranhão (CEMAR). The APC was funded by CELPA and CEMAR.

Acknowledgments: The authors acknowledge the support provided by the Post-Graduate Electrical Engineering Program PPGEE/UFPA.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

ATP	Alternative Transients Program
BIL	Basic Isolation Level
CB	Capacitor Bank
CMT	Cross Mean Table
GA	Genetic Algorithm
V_{CFO}	Critical Flashover Voltage

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