Evaluating Optimum Arrester's Locations in HV and EHV Networks Using Simulation Optimization to Suppress Switching Surge Overvoltages

B. Vahidi, M. R. Bank Tavakoli and S. H. Hosseinian

ABSTRACT

In this paper, the main aim is to introduce a regular procedure to select the location of arresters (voltage limiters) in a way to optimally confine the risk of flashovers in a given high voltage network. Mathematically, simulation optimization is used to create an acceptable meta model from a real model which, on its own, is created to represent a real high voltage network in a transient analyzer program, The proposed meta model is a three layer perceptron neural network which is learned to estimate the risk function with arrester locations as inputs and network risk of flashover as output. Genetic algorithm is then invoked to locate the best position of arresters. The proposed method is then accomplished to set the location of 5 identical arresters in Iranian South East 400 kV network and the results are shown to be acceptable by simulating the real model of this network.

KEYWORDS

Simulation optimization, Neural net, Genetic algorithm, Switching overvoltages, Arresters, ATP.

1. INTRODUCTION

Switching overvoltages are one of the most important aspects for insulation design and coordination in high (HV) and extra high voltage (EHV) networks. Proper limiting of these switching overvoltages will result in better line performance and fewer switching overvoltage outages. There are relatively high number of research papers on estimating the overhead line performance due to switching overvoltages even phase to ground [1], [2] and [3] or phase to phase overvoltages [4], [5] and [6]. Application of arresters in high voltage networks is also studied and some standards are created as a guide for arrester installations [7]. Recently, some investigations have been made to evaluate arrester's positions in a distribution cable network to minimize the lightning surge risk of failure [8]. Also, in a different work, the authors in [8] have used artificial neural networks to predict the lightning failure risk of same distribution cable network [9]. Although for an extra high overhead line the switching overvoltages are more important and switching overvoltage risk evaluation requires different engineering aspects to be taken into account [1].

In this work, a simulation optimization method is used to solve the problem of locating best positions for assumed number of arresters in HV and EHV networks. In simulation optimization method, a second level model called Meta model is constructed based on an actual model (first level model) which represent an existing physical system. All the analysis is performed on Meta models and the results is then compared with the results of first level model or physical system [10]. In this work, this method is used based on neural network and regression (only for comparison) as Meta models. Genetic algorithm is also used to find the optimum positions for some arresters with the goal of minimizing switching surge risk of failure in the network. The position of arresters is discontinuous and there are some nodes of interest which candidate for arresters. There are four steps to obtain optimum positions. First, statistical data is gathered from network with simulation, using a transient program. In this stage, in each constant position of arresters, switching overvoltages are obtained by randomly switching the circuit breakers within their pole closing span. Using these data, a suitable probability distribution function for overvoltages in all nodes, can be constructed. Second, risk of failure is calculated from data acquired and therefore

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goal function for some positions would be available. Third, a three layer perceptron and a regression equation would be allocated to learn these statistical data. These Meta models are the core of optimization algorithm, i.e., genetic algorithm to get optimum positions as the fourth stage. In each step, there are measures that ensure good precision for predictions and results. The Iranian South East 400 kV network is the subject of simulation in ATP to collect statistical of overvoltages. All numeric data processing is then accomplished by use of MATLAB to obtain the optimum positions of arresters.

The rest of paper is organized as follows. In section 2, the details of collecting the overvoltages statistical data is described. The procedure for computing the goal function values, i.e., switching overvoltage risk of flashover in nodes and network is presented in section 3. Sections 4 and 5 describe the Meta models and genetic algorithm respectively. In section 6, the overall optimization procedure is briefly reviewed. The results of simulation and optimization procedure for the Iranian South East 400 kV network is presented in section 7. Finally, section 8 concludes the paper.

2. Statistic Data Acquisition

With an electromagnetic transient program, power system can be modeled and maximum switching overvoltages on network nodes can be obtained, when arresters are in determined positions. The ideal study should assume a node on each tower of high voltage or extra high voltage line which can be candidates to mount arresters. Practically, such an assumption will increase the computation volume dramatically. Therefore, it is applicable that lines or cables divide into some sections and between each two sections, a fictitious node can be inserted [11], and these nodes determine the risk of failure in individual line and total network. To avoid large number of nodes for simple networks, the number of sections remains low. In this paper, based on the work of [10], all lines can be divided into three equal sections and two nodes inserted in each line (Fig. 1). Switching actions to close the line can be implemented by statistical switches having Gaussian or uniform switching action distribution function. To model the worst case, open ended lines may be considered and transformers and other equipments may be ignored. In each cases, arresters locations are selected randomly and a random generator determines the nodes for arresters in next case. Afterward, with a constant number of arresters, maximum overvoltages produced in each node, in each position of arresters, will be available. The number of switching actions when arresters are in determined locations and the number of different cases due to changing arresters positions should be selected properly to draw out a well conditioned Meta Model to fit the real model as precise as possible. All these statistical sampling can be done step by step (Fig. 2) and enough information for each node and each case to determine overvoltages probability distribution function parameters can be collected easily.

3. Goal Function: Risk of Failure

After gathering enough data, goal function should be evaluated. The most convenient aim in such processing is to reduce damage probability in network.

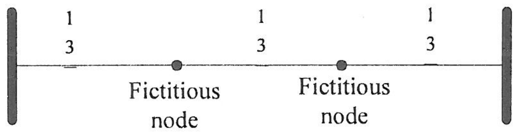

Figure 1: Fictitious nodes and their location on the line.

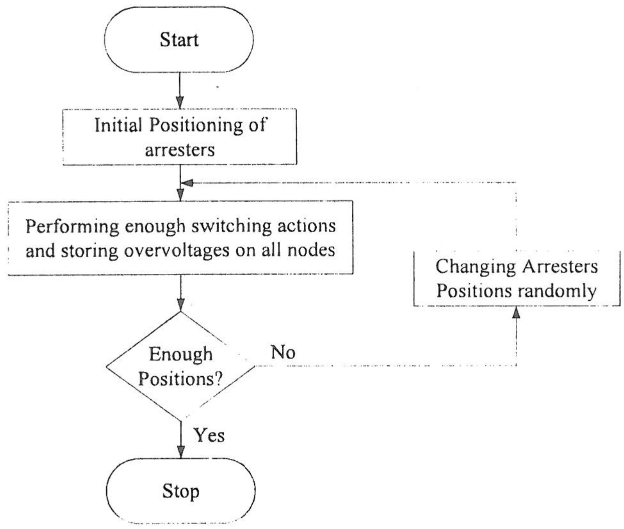

Figure 2: Data acquisition flowchart.

Risk of Failure is the probability of danger in nodes. Based on this probability, another criterion is usually defined to represent the overhead line performance which is switching surge flashover rate (SSFOR) [11]. Using these criteria, a good goal function can be derived for the network of study, considering all lines can be established. In the following sections, first risk of failure for one tower is presented and then the SSFOR for network will be derived.

A. Risk of Failure in Each Node

To determine the risk of failure in one node, two probabilistic functions are required: probability of disruptive discharge (strength function) and probability density of switching overvoltages (stress function).

According to insulation strength of the node, occurrence of overvoltages may lead to damage or not. Probability of disruptive discharge is in the form of (1).

$$F(v) = \frac{1}{\sigma_{in}\sqrt{2\pi}} \int_{-\infty}^{v} \exp\left[-\frac{(V-\eta_{in})^2}{2\sigma_{in}^2}\right]\cdot dV \qquad (1)$$

where

$F(v)$ is probability of disruptive discharge;

η_{in} is the critical flashover voltage (CFO);

σ_{in} is the standard deviation.

Risk of failure in each node, Fig. 3, can be calculated from the area under function produced from crossing two probabilistic functions. Expression for risk of failure is in the form of equation (2).

$$R = 1/2 \int_{E_0}^{E_m} F(v) \cdot f(v) \cdot dv \qquad (2)$$

where

E_0 is the minimum voltage to consider switching overvoltage usually 1 pu of nominal line to neutral voltage and E_m is the maximum switching voltage may occurs; $f(v)$ is the probability density of switching overvoltages.

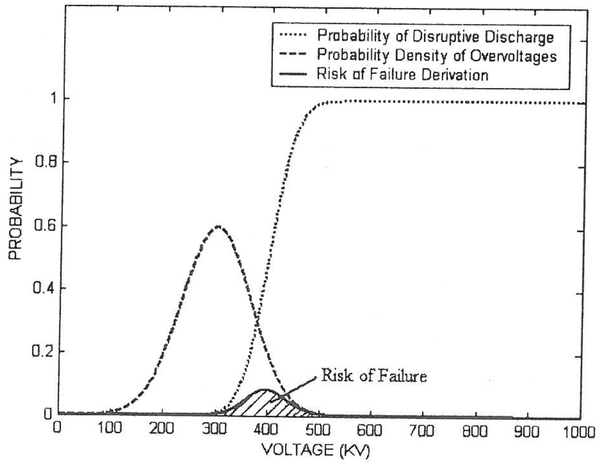

Figure 3: Risk of failure in a node of a network.

Usually, normal distribution function is considered to determine switching overvoltages, although Weibull distribution function can be used as well. If a normal distributed function is to be used to represent overvoltage probability density function according to equation (3), mean and standard deviation should be determined.

$$f(v) = \frac{1}{\sigma_{ov}\sqrt{2\pi}} \exp\left[-\frac{(v-\eta_{ov})^2}{2\sigma_{ov}^2}\right] \qquad (3)$$

η_{ov} is overvoltage for which probability of occurring overvoltages less than or equal it is 50%;

σ_{ov} is the standard deviation of data.

Parameters a and b are required as equation (4) If a Weibull probability density function is assumed [12].

$$f(v) = ba^{-b}v^{b-1}\exp\left[-(v/a)^b\right], v \geq 0 \qquad (4)$$

The integral of equation (2) is multiplied by $1/2$ because the insulation strength for negative polarity is significantly larger than that for positive polarity. Thus, negative switching overvoltages can be ignored and total integral should be multiplied by $1/2$.

It reveals from (2) that risk of failure evaluation needs numerical integration and for each positions calculation volume will be large. After evaluating risk in each node, risk of failure in network could be determined from risks in total nodes.

B. Risk of Failure in Network

Risk of failure in network is calculated using risk of failure of the nodes. For a transmission line, there are many towers that may produce flashover on switching actions. Essentially, all on these towers are nodes in which faults may occur. Also, just some of these nodes are selected to place arresters. There are two possibilities to define network goal function, one to consider just the interest nodes and define risk of failure as nodes risk of failure weighted average, equation (5).

$$R_{netw} = \frac{1}{\sum_{j=1}^{M} t_j} \cdot \sum_{i=1}^{M} t_i \cdot R(i) \qquad (5)$$

Using this criterion has the advantage that the sensitivity of goal function to arrester changing is high and optimization procedure would be easier. But this goal function does not represent the real switching risk of failure in the network, because there are many others nodes that may lead to flashover. The other criterion can be the switching surge flashover rate per line of the network. The switching flashover rate of an overhead line having n towers is [11]:

$$SSFOR = (1/2)\int_{E_0}^{E_m}\left[1-\prod_{i=1}^{n}(1-p_i)\right] \cdot f_s(v) \cdot dv \qquad (6)$$

where

$SSFOR$ is switching risk of failure of overhead line per switching action;

E_0 and E_m are the min and max voltages for integration as defined in previous section; p_i is the probability of flashover at tower i for specified switching overvoltage and $f_s(v)$ is the probability density function at the opened end of the line.

If the voltage profile in the line be flat, then all p_i in equation (6) are equal. Actually, the switching voltage is lower at the switched end and higher at the other end of the line.

Also, for single phase switching actions, the probability of flashover in each tower may be calculated using brute force method as (7).

$$P(F) = [1-(1-p_A)(1-p_B)(1-p_C)] \qquad (7)$$

where

$P(F)$ is the probability of flashover in each tower;

p_A, p_B and p_C are the probability of flashover in phase A, B and C, respectively. Thus, the probability of flashover on each line of network can be derived using (6) and (7). To prepare the overall risk of the network, one can use the average risk of failure of all lines.

$$R_{net} = (1/N)\sum_{i=1}^{N} SSFOR_i \quad (8)$$

where

R_{net} is the flashover rate per switching action per overhead line;

N is the number of overhead lines in the network and

$SSFOR_i$ is the switching surge flashover rate of line i.

Using R_{net} as goal function, the aim is to explore a proper Meta Model from sample data and find the best places to mount the arresters.

4. META MODELS

The first operators to implement simulation optimization are Meta models [13]. A Meta model simply is a function that substitutes the real problem. The more precise the Meta model, the more accurate the final results. Meta models are used to simplify the solution process of complex problems such as Risk of failure, because the real goal function in this function is practically unavailable in the same time for all positions. In this works, two Meta models are used. The accurate model is a three layer perceptron neural net to substitute risk of failure function and for comparison regression is used to evaluate risk of failure as well [14].

Some test points are suggested to examine the goodness of the model. After learning process, the Meta model can be used to predict the test positions. If mean square error of these predictions be small enough, then Meta model is qualified to be used as the core of optimization algorithm (Fig. 4).

A. Neural Net

First Meta model mostly used in this area is a feed forward neural net named three layer perceptron, Fig. 5 [15] and [17]. This neural net and back propagation learning methods together produce a powerful approximator [16] Hidden layer of the net normally has sigmoid function. Also, it can be used for output layer because risk values are between 0 and 1 and the sigmoid function lay in the range.

Inputs are arrays with cell number equal to the total node number in power system. Cells take the value of zero or one according to existence or nonexistence of arrester in each node.

Desired outputs are risk of failure in each position. With this binary encoding, optimization process will be easier and simpler.

In back propagation with momentum learning method [18], network parameters will be changed according to (9).

$$\begin{aligned} w_l^{k+1}(i,j) &= w_l^k(i,j) - \\ &\alpha \cdot \frac{\partial R}{\partial w_l^k(i,j)} + \gamma \cdot \Delta w_l^{k-1}(i,j) \\ b_l^{k+1}(i) &= b_l^k(i) - \\ &\alpha \cdot \frac{\partial R}{\partial b_l^k(i)} + \gamma \cdot \Delta b_l^{k-1}(i) \end{aligned} \quad (9)$$

where

$w_l^k(i,j)$ is the cell in row i, column j of weight matrix in layer l and in learning k th pattern;

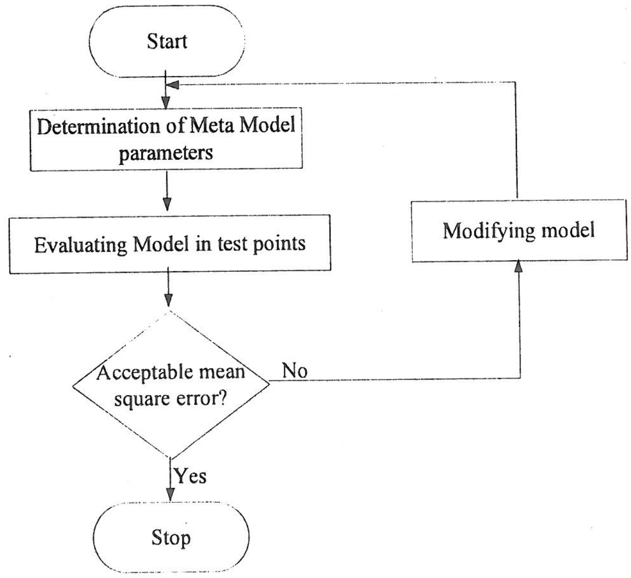

Figure 4: Meta Model evaluating algorithm.

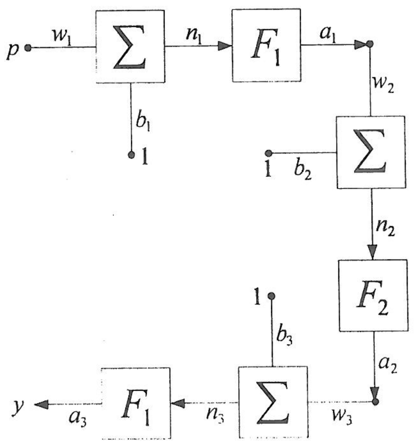

Figure 5: A three layer perceptron.

R is learning criterion function typically square error of output layer; $b_l^k(i)$ is i th cell of bias array of layer l in learning process of k th pattern; α is learning rate factor and γ is the term of momentum; $\Delta w_l^{k-1}(i,j)$ and $\Delta b_l^{k-1}(i)$ are (i,j) th weight & i th bias errors of layer l in learning $k-1$ pattern. After reaching the goal of learning, if neural net prediction errors for test points was not acceptable learning process restarted after changing 1) goal of learning, 2) number of patterns, 3) number of middle layer neurons or 4) initial values of weight and bias arrays.

B. Regression

Although with nonlinear structure of power system, regression does not seem to be a good model. But to produce the possibility of comparison and simplicity of using regression, it can be used to model risk of failure.

A regression expression may be in the form of (10).

$$R_{reg} = a_1 x_1 + a_2 x_2 + \cdots + a_m x_m \qquad (10)$$

where

a_i is ith regression coefficient;

x_i is existence variable in node i and can be defined as (11).

$$x_i = \begin{cases} 1 & \textit{Arrester exist in node i} \\ 0 & \textit{Arrester doesn't exist in node i} \end{cases} \qquad (11)$$

Equation (10) is written for arrester number equal or greater than one and dc term of equation ignored. When number of data is bigger than nodes, coefficients developed from statistical equations [11] and when data are in the range of nodes, coefficients explored from linear equation solving.

Optimization process with regression is totally simple. The only constrain is that arrester existence variable should be in the set $\{0,1\}$. We just need to find minimum coefficient and set its x_i to 1.

5. Optimization Method: Genetic Algorithm

Genetic algorithm is an evolutionary computing method which finds the best solution for the environment by searching the solution space with a probabilistic exchange of information between each individuals or chromosomes. [19] and [20].

A typical genetic algorithm with initial population and operators explore good results for problem, Fig. 6.

Although the main steps of genetic algorithm which is applied on the risk function in this paper is similar to literatures [20] and [21], there are some adoption for this specified goal function which are listed as follows:

a) Goal function in genetic algorithm will be neural net model of risk function. Because of the minimization nature of problem, rank selection can be used to select best individuals and roulette wheel used to select the chromosomes with proper probability [21]. Probability of selecting i th chromosome is in the form of (12)

$$p_s = \frac{fitness(i)}{\sum_{k=1}^{S} fitness(k)} \qquad (12)$$

where $fitness(i)$ is fitness number allocated to chromosome and S is total number of individuals in generation. Two chromosomes are selected in each generation to produce offsprings. One is the best individual and other elected randomly. Selection also used to find migrating chromosomes to next generation till total population remains constant.

b) Mutation is used to give this chance to algorithm to produce out of order individuals which may be better or not. In the case of finding arrester optimum positions, after binary encoding with existence variable equation (10), genetic algorithm can easily be used to optimize the goal function. In the case of arresters optimum position problem, there are two groups of individuals.

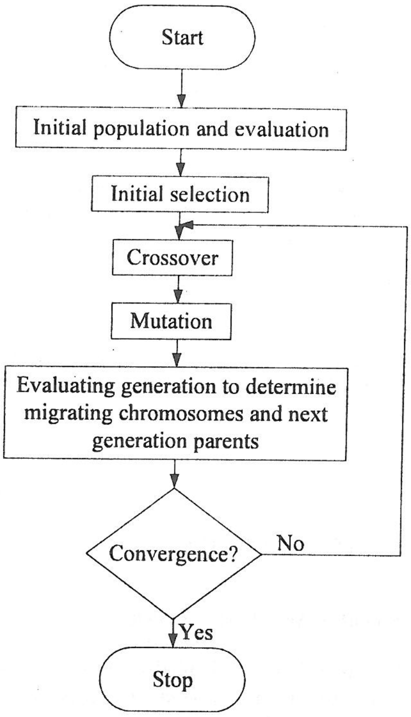

Figure 6: A simple genetic algorithm flowchart.

Some chromosomes may have more or less ones in their string than suggested constant number of arresters. This group has obligatory mutation to fix number of ones. Here according to number of ones, some zero or one will be changed.

For chromosomes which have accurate number of ones in their string of genus, mutation is used to avoid stopping algorithm in very good chromosomes and some of these individuals have mutation with changing one or two genus of their strings. Therefore, the rate of mutation differs in generations and depends on the proper chromosomes of the generations.

6. Optimization Procedure

With details mentioned before, the optimization procedure is presented through the flowchart of Fig. 7. The steps of flowchart are as the same described before, i.e., after data acquisition the meta model is constructed with acceptable error in its patterns prediction, then utilizing an optimization methods the suggested arresters positions are identified and if these locations produce acceptable results when simulating the real network, the procedure should stop. Otherwise, the learning procedure restarted after modifying model or learning procedure parameters and process will be continued. The optimization algorithm also is repeated with different starting points and different initial population to make it sure that same minimum point is derived.

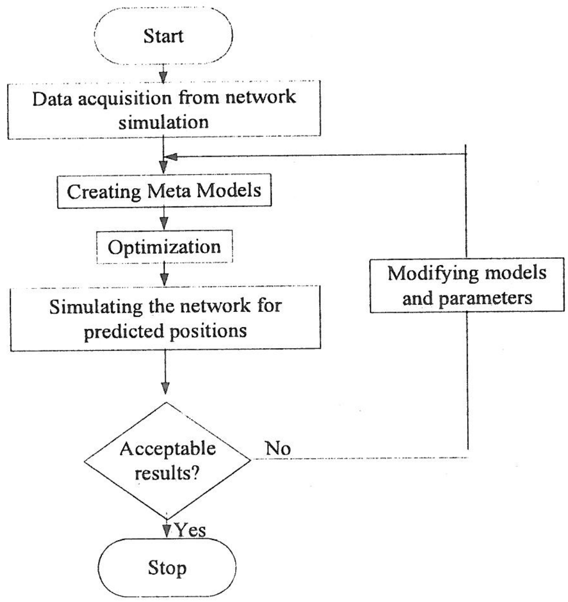

Figure 7: Overall process flowchart.

7. RESULTS FOR SAMPLE NETWORK

Simulation optimization described before, was used to obtain optimum positions of five arresters which should locate in the Iran South East 400 kV network, (see Fig. 8). In addition to substation names and lines codes, all nodes have numbers that presented without brackets. Also, a number, which is encircled, is allocated to each line. The network composes of four 400 kV overhead lines and BandarAbbas power plant at the end of lines. The other end of radial lines in Fig. 8 are assumed open to consider the worst case of overvoltages, also reactors, transformers and other substation components have been ignored. The substation surge arresters are removed to test the algorithm for placing the arresters in the end of open lines.

This method makes addressing easier. Network simulation was done with WATCOM ATP/EMTP and graphical interface ATPDRAW 3.6 [22] and [23].

Overhead lines are modeled to study transient behaviors. Data for modeling lines, switches and arresters are presented in Appendix I.

In all cases, there were 5 arresters and their positions were changed. For each position of arresters, 400 single pole switching action on line breakers in Fig. 8, were performed and 400 overvoltage values explored from simulation. Fig. 9, represent the empirical cumulative distribution function (CDF), normal assumed CDF and Weibull assumed CDF, for overvoltage in node 4, when arresters were located in nodes 2, 3, 5, 8, 11.

There is not much difference between these two distributions and both are the same to represent switching overvoltages. The Weibull distribution was selected to calculate risk of failure. Data from simulations are delivered to MATLAB 7.1 [24] after storing in Microsoft Excel as interface software. All statistical calculations, Meta models and optimization are simulated in this software. Risk of failure then computed using (6) with numerical integration for different assumption on insulation strength and arrester different positions. For simplification, the voltage profiles along the lines are assumed to be stepwise and for all towers before a node in Fig. 8, the switching overvoltage of that line is assumed. Lines were divided into three equal parts and two fictitious buses supposed. Therefore, a three step voltage profile on each line is considered. If a flat voltage profile along the line is assumed, the flashover rate will be much higher comparing the stepwise voltage profile assumption.

Fig. 10, represent these two cases for flashover per switching action per line or network *SSFOR*. Totally, 80 different positions of arresters were simulated which are listed in Appendix II.

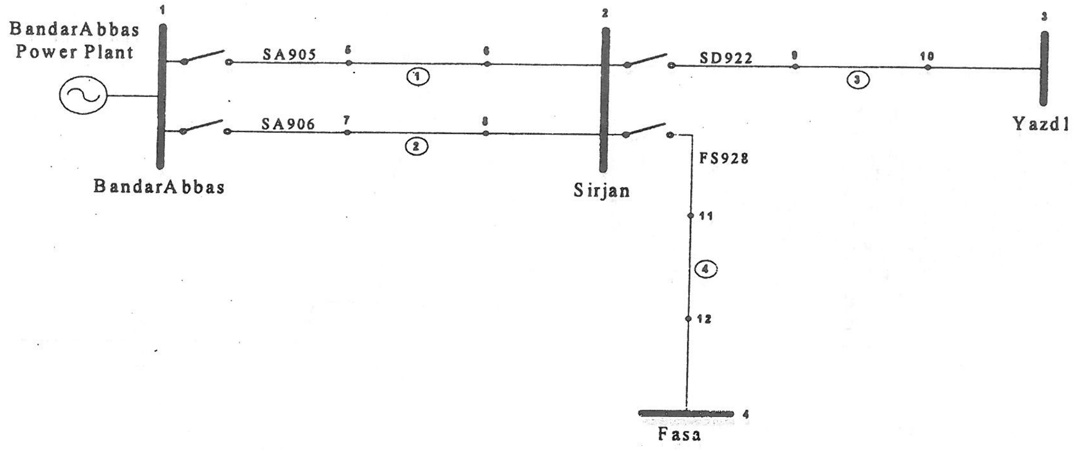

Figure 8: Iranian South East 400 kV network.

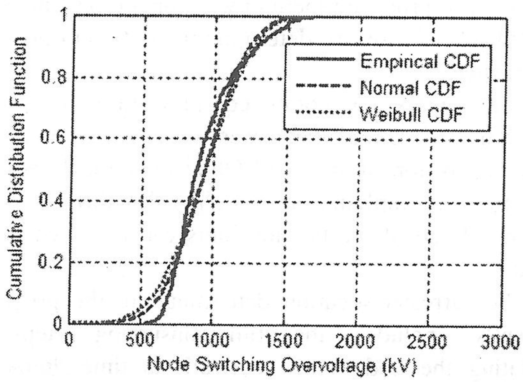

Figure 9: Empirical, normal and weibull CDFs.

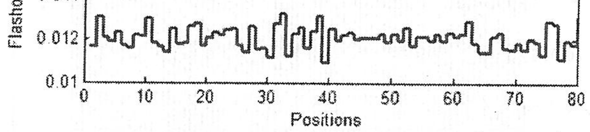

Figure 90: Effect of voltage profile on network switching flashover rate.

Figure 11 shows risk of failure of the network for these 80 positions, when BSL is 1050 kV or 950 kV. In this figure, the standard deviation σ/CFO is 5%.

In all optimization procedure the BSL insulation strength is assumed to be 1050 kV and standard deviation is supposed to be 5%. Equation (11) is useful to evaluate $CF\Phi$ 25] and [26].

$$BSL = CFO(1-1.28\frac{\sigma_f}{CFO}) \tag{11}$$

where

BSL is basicswitching impulse insulation level;

CFO is critical flashover voltage; σ_f/CFO is per unit standard deviation, which is considered 5% for tower insulation and 7% for station class insulation [27]. Fig. 12 shows the comparison for effects on risk of failure between these two standard deviation values. From statistical data, 70 positions are selected to obtain coefficients of regression and to be the learning patterns of the neural net which is a three layer feed forward net with all sigmoid function and has 12 neurons in layer one, 3 in layer 2 and one neuron in output layer. Scaled conjugate gradient back propagation algorithm was used for training the neural net. Performance function (mean square error) of neural net is depicted in Fig. 13.

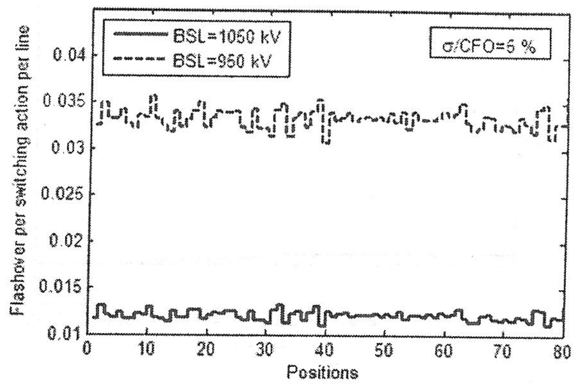

Figure 11: Switching flashover rate in different positions and effect of BSL.

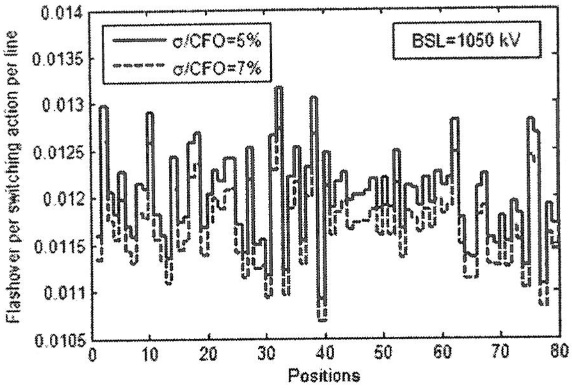

Figure12: Switching flashover rate in different positions and effect of pu standard deviation.

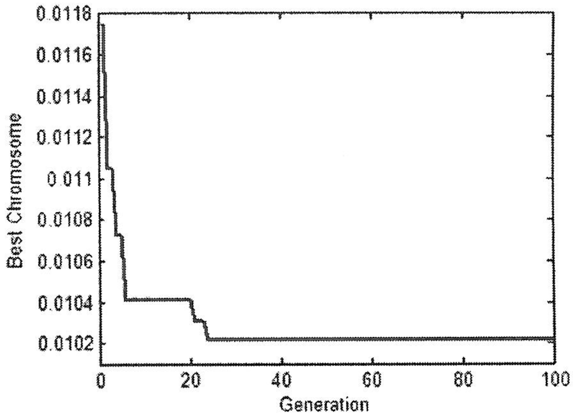

Figure 104: Genetic algorithm convergence.

After training, the mean square error for remaining 10 points that is predicted by neural net was 0.1%. Therefore the proposed neural net is qualified to be used in optimization process. A genetic algorithm with 45 initial population and 12 offspring per generation has the role of optimizer. Mutation is done for 5 individuals per generation excluding the individuals that have incorrect number of 1 in their strings. Convergence process is shown in Fig. 14.

Optimum positions predicted by neural net are nodes 3, 4, 5, 7 and 9 with predicted flashover per switching action per line value of 0.0102. Simulation by ATP with arrester location in predicted optimum position (3, 4, 5, 7 and 9) gives*SSFOR* value of 0.0098. This value of *SSFOR* is less than all test positions similar *SSFOR* values, Fig. 15. Regression method prediction is 0.0034 and is very far from real simulation result of 0.011 which is bigger than values of some test points and isn't acceptable as optimum point. Fig. 16 creates a comparing scheme between results. Therefore optimum position as predicted by neural net can be acceptable for an evaluation of minimum *SSFOR* in the network. What should be noted is that the algorithm placed the arresters on the line 3 and 4 ends as expected, to confine the open end line overvoltages.

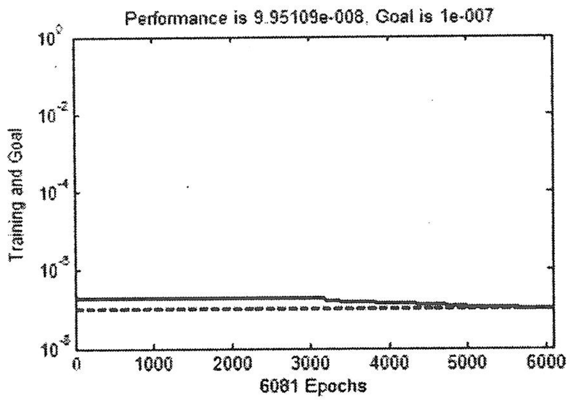

Figure13: Neural net performance.

8. Conclusions and Discussions

A neutral net-genetic algorithm based simulation optimization was proposed to find best positions for arresters to set risk of failure of the network as less as possible. The proposed method was applied on Iran South East 400 kV network to determine the optimum positions of 5 arresters.

In this work, a combined procedure of genetic algorithm and neural nets was used to compute the optimum position of arresters. Other theoretical approach may consist of applying genetic algorithm directly on the network. Practically following hints can be given in this regard:

1) For arrester location determination, the procedure inherently includes the time-consuming steps for simulating the under-study network in time domain to obtain overvoltages. Applying the genetic algorithm directly to the model then consume a lot of time which makes the procedure inapplicable. The time for collecting sample data is much more relevant and there is the possibility to concentrate on the samples which models the scenarios that are more important according to expert engineering guidelines.

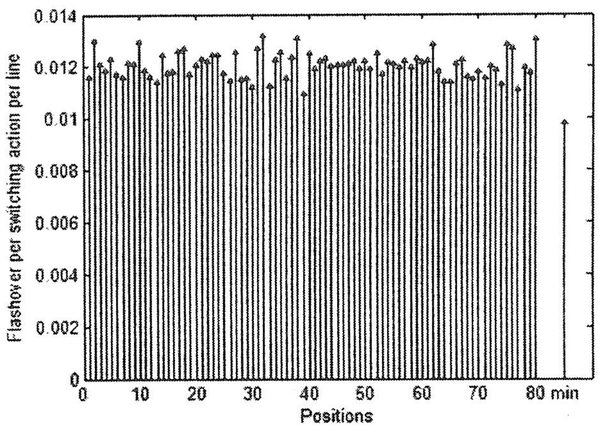

Figure 115: Comparing simulated positions and optimum positions predicted by neural net.

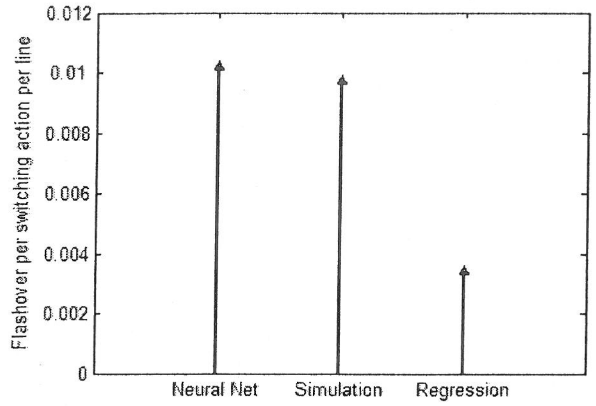

Figure16: Comparing Meta models with real simulation.

2) With the proposed method of simulation optimization, the overvoltage estimation and optimization steps become independent of each other. Therefore, if there are experimental values of overvoltages available (via fast transient recorders), this procedure is still applicable.

To be noted is that the rate of sampling is not important in this case because the problem is in the design stage of the network. Nevertheless, the number of samples should be selected accordingly and if the error of prediction of Meta models is not acceptable, the samples will increase until achieving good prediction errors. The optimum location of arresters which is obtained in this procedure will not be exact due to inevitable errors in different stages. But from the engineering point of view, the results will be acceptable as the sensitivity of analysis is not too high [11].

Selecting proper Meta Model and the way of training the model is very important to explore acceptable results. In each step of process the goodness of Model and training procedures should be tested to ensure the goodness process progress.

9. Appendix 1

In this appendix, the network equipment parameters (according to ATP models) are presented.

TABLE 1
OVERHEAD LINES SPECIFICATIONS

Parameters		Names and Values	
		SA905, SD922, FS928	SA906
Average Span Width (m)		400	400
Conductor Types	Phase	MARTIN	CARDINAL
	Shield	7NO8AW	7NO8AW
Bundles	Number	3	2
	Spacing (cm)	50	50
	Alpha (deg)	90	180
Phase A	Y (m)	31.5	31.5
	X (m)	-18.6	-18.6
	Average Sag (m)	5	5
Phase B	Y (m)	31.5	31.5
	X (m)	0	0
	Average Sag (m)	5	5
Phase C	Y (m)	31.5	31.5
	X (m)	18.6	18.6
	Average Sag (m)	5	5
Shield Wire1	Y (m)	44	44
	X (m)	-9	-9
	Average Sag (m)	5	5
Shield Wire2	Y (m)	44	44
	X (m)	9	9
	Average Sag (m)	5	5

TABLE 2
CONDUCTOR PARAMETERS

Conductor	Inner Radius (cm)	Outer Radius (cm)	DC Resistance (ohm/km)
MARTIN	0.6	1.81	0.0425
CARDINAL	0.51	1.52	0.0599
7NO8AW	0	0.49	1.49

TABLE 3
LINE LENGTH

Line	Length (km)	Approx. Number of Towers
SA905	312	780
SA906	314	786
SD922	296	741
FS928	235	588

TABLE 4
SWITCH PARAMETERS

Distribution	Gaussian
Mean (s)	0.04
Dev (s)	0.008

Table 5
Arrester Parameters

Nominal Voltage (kV)	360
MCOV (kV)	289
V-I Characteristics	
I (kA)	V (kV)
1e-10	1e-10
1e-5	404
0.5	693
1	727
2	740
3	785
5	802
10	836
20	920
40	1064

10. Appendix 2

In each position, five nodes are shown that arresters are located in them when simulating the network for evaluating risk of failure.

TABLE 6
DIFFERENT LOCATIONS FOR ARRESTERS

POS. NO.	NODES NO.	POS. NO.	NODES NO.
1	2, 5, 7, 10, 12	41	1, 2, 6, 7, 8
2	2, 3, 5, 8, 11	42	1, 2, 6, 8, 9
3	1, 4, 6, 9, 12	43	1, 2, 6, 8, 11
4	1, 3, 4, 6, 7	44	1, 2, 6, 10, 12
5	2, 3, 5, 8, 9	45	1, 2, 7, 8, 11
6	4, 8, 9, 10, 11	46	1, 2, 8, 9, 12
7	2, 6, 8, 10, 11	47	1, 2, 8, 10, 11
8	1, 4, 8, 11, 12	48	1, 2, 8, 11, 12
9	2, 3, 4, 6, 9	49	1, 3, 4, 5, 6
10	1, 5, 6, 10, 11	50	1, 3, 4, 5, 7
11	1, 2, 7, 9, 12	51	1, 3, 4, 5, 12
12	3, 5, 8, 10, 12	52	1, 3, 4, 7, 11
13	3, 5, 7, 9, 11	53	1, 3, 4, 8, 12
14	2, 4, 6, 7, 9	54	1, 3, 4, 9, 11
15	1, 5, 9, 10, 12	55	1, 3, 5, 6, 8
16	2, 4, 5, 7, 10	56	1, 3, 5, 9, 10
17	2, 4, 5, 9, 10	57	1, 3, 7, 8, 9
18	4, 5, 6, 9, 11	58	1, 3, 7, 8, 10
19	1, 2, 8, 10, 12	59	1, 3, 10, 11, 12
20	1, 3, 6, 7, 10	60	1, 4, 5, 7, 11
21	1, 2, 3, 5, 8	61	1, 4, 5, 9, 10
22	1, 2, 3, 7, 10	62	1, 4, 5, 10, 11
23	3, 4, 6, 9, 12	63	1, 4, 6, 10, 12
24	1, 2, 3, 8, 10	64	1, 4, 8, 9, 10
25	1, 2, 4, 5, 6	65	1, 4, 8, 9, 11
26	1, 2, 4, 6, 9	66	1, 5, 6, 11, 12
27	1, 2, 4, 6, 11	67	1, 5, 9, 11, 12
28	1, 2, 4, 6, 12	68	1, 6, 7, 8, 10
29	1, 2, 4, 7, 8	69	1, 6, 7, 10, 11
30	1, 2, 4, 7, 10	70	1, 6, 8, 10, 12
31	1, 2, 4, 7, 12	71	1, 7, 8, 9, 12
32	1, 2, 4, 8, 10	72	1, 7, 10, 11, 12
33	1, 2, 4, 9, 10	73	2, 3, 4, 5, 6
34	1, 2, 4, 11, 12	74	2, 3, 4, 5, 9
35	1, 2, 5, 6, 9	75	3, 4, 5, 7, 8
36	1, 2, 5, 6, 10	76	2, 3, 5, 6, 12
37	1, 2, 5, 6, 11	77	2, 3, 5, 7, 9
38	1, 2, 5, 6, 12	78	2, 3, 5, 9, 12
39	1, 2, 5, 8, 11	79	2, 3, 8, 10, 11
40	1, 2, 5, 11, 12	80	2, 3, 8, 10, 12

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