Journal of Energy

VOLUME 60 | 2011

journal homepage: http://journalofenergy.com/

Application of ANN and Genetic Algorithm for Evaluation the Optimum Location of Arresters on Power Networks due to the Switching Overvoltages

Reza Shariatinasab[1], Behrooz Vahidi and Seyed Hossein Hosseinian
Amirkabir University of Technology
Iran

Akihiro Ametani
Doshisha University
Japan

SUMMARY

Switching surges are of primary importance in insulation co-ordination of EHV lines, as well as in designing insulation of apparatuses. The magnitude and shape of the switching overvoltages vary with the system parameters, network configuration and the point-on-wave where the switching operation takes place. This paper presents an artificial neural network (ANN) based approach to estimate the peak value of overvoltages and the global risk of failure generated by switching transients during line energizing or re-energizing in different nodes of a power network. Then a genetic algorithm (GA) based method is developed to find the best position of surge arresters on power networks so as to minimize the global risk of the network.

KEYWORDS

Switching surges - Artificial neural network (ANN) - Genetic algorithm (GA) - Surge arrester - Risk analysis - EMTP/ATP Draw.

1 INTRODUCTION

The insulation level of HV and EHV systems is largely determined by the magnitude of switching overvoltages. Switching surges are a transient overvoltage in which a slow front, short duration, and oscillatory is generated [1]. The objective of simulating switching overvoltages in a power system network is to help for a proper insulation co-ordination as well as for designing the insulation level for different equipment and components of the system. This would lead to minimize damage and interruption to service as a consequence of transient overvoltages. For long EHV lines, pre-insertion resistors (PRI) traditionally are used to limit switching overvoltages. In recent years some trends have been to find alternatives to PRI by active use of arresters or by controlled switching [2,3]. This paper presents an ANN application for estimation the failure risk of power networks under switching transients. Then a method based on GA is developed in order to find the optimum location of surge arresters on a power network to minimize the global risk of insulation in the network. Results of the studies are presented for a sample EHV network of Iranian grid to illustrate the proposed approach.

1- Corresponding Author: Shariatinasab@aut.ac.ir

2 RISK OF FAILURE

The failure risk of a network component due to switching transient presents the probability that the switching surge exceeds the withstand voltage. It is assumed that the probability of disruptive discharge of insulation is given by a normal cumulative probability function:

$$P(V)=\frac{1}{\sigma.\sqrt{2\pi}}\int_{-\infty}^{V}\exp[-\frac{(V-V_{50\%})^2}{2\sigma^2}].dV \qquad (1)$$

where *P(V)* is the probability of disruptive discharge; $V_{50\%}$ is the voltage under which the insulation has a 50% probability to flashover or to withstand and σ is the standard deviation. While we do not have a known function in order to obtain the statistical distribution of switching overvoltages, there is the statistical switching capability of EMTP/ATP which allows us to generate the statistical distribution of switching overvoltages in the network nodes. It is assumed that the switching overvoltages distribution is the normal density function:

$$f(V)=\frac{1}{\sigma.\sqrt{2\pi}}.\exp[-\frac{(V-V_{50\%})^2}{2\sigma^2}] \qquad (2)$$

where *f(V)* is the probability density of overvoltage occurrence; $V_{50\%}$ is the overvoltage for which the probability density of occurrence is 50% and σ is the standard deviation. The failure risk of each interesting network node is calculated by taking the distribution of applied overvoltages together with the distribution of its withstand voltage level and is expressed as [4]:

$$R=\frac{1}{2}\int_{E_0}^{E_m} f(V).P(V).dV \qquad (3)$$

where *R* is the failure risk, *f(V)* the probability density of overvoltage occurrence and *P(V)* is the probability of disruptive discharge. E_0 is the minimum and E_m is the maximum voltage that may be occurred in the system. On any transmission line there are *n* towers that may lead to flashover by switching operations. Essentially all of these towers are nodes where fault may occur. However, only some of these nodes are selected to place arresters, i.e. interesting nodes. There are two possibilities to define global risk of the network. One may only consider the interesting nodes and define the global risk of the network, R_{global}, by:

$$R_{global}=\frac{1}{\sum_{j=1}^{m} t_j}.\sum_{j=1}^{m} t_j.R(j) \qquad (4)$$

where *R(j)* is the risk of each interesting node, t_j relative weight of each node correspond to the most important node considering the economical criteria, and *m* is the number of interesting nodes. But this function does not represent the real failure risk of switching in the network, because there are many other nodes that may lead to flashover and should be considered. The other criterion can be the switching surge flashover rate of line having *n* towers [5]:

$$SSFOR=\frac{1}{2}\int_{E_0}^{E_m}\left[1-\prod_{i=1}^{n}(1-P_i)\right].f_s(V).dV \qquad (5)$$

where *SSFOR* is switching surge flashover rate of overhead line per switching operation, E_0 and E_m are as defined previously, P_i is the probability of flashover at tower *i* for specified switching overvoltage and $f_s(V)$ is density function of overvoltages at open end of the line. If voltage profile along the line be flat, then all P_i in (5) are equal. Then, to prepare global risk of the network, one can use the average flashover rate of all lines in the network, so:

$$R_{global}=\frac{1}{N}\sum_{i=1}^{N} SSFOR_i \qquad (6)$$

where R_{global} is flashover rate per switching operation per line, i.e. global risk of the network, $SSFOR_i$ is the switching surge flashover rate of line *i*, and *N* is number of lines in the network.

3 ANN DESIGN, TRAINING AND TESTING

For an existing system the main factors which affect the peak value of switching overvoltages are switching angle, line length, source strength and shunt reactor. It should be mentioned that a single parameter often cannot be regarded independently from the other important influencing factors. This forbids the derivation of precise generalized rule or simple formula applicable to all cases [6]. Also depending on the surge arrester's location on the network, distribution of overvoltages will be different. Then for any power system, different location of arresters will lead to different values of overvolages and global risk of the network. An ANN can help us to estimate the peak value of switching overvoltages and to evaluate the global risk of the network for each position set of arresters. An ANN is programmed by presenting it with training set of input/output patterns. ANN can learn the relationship between the inputs and outputs. The ANN in this work has the feed forward Multilayer Perceptron (MLP) architecture. A MLP trained with the back propagation algorithm may be viewed as a practical vehicle for performing a nonlinear input/output mapping of a general nature. The MLP architecture proposed in this work, Fig. 1, is composed of single hidden layer and output layer. It is capable of solving difficult and complex problems [7].

The inputs of the proposed ANN are arrays with cell numbers equal to the interesting nodes of the power network. Cells number can take the value of zero or one according to existence or nonexistence of arrester in each relative node. The ANN outputs are peak value of switching overvoltages and/or global risk of the network correspond to each position set of arresters. Supervised training of ANN is a usual training paradigm for MLP architecture. Fig.2 shows the supervised learning of ANN for which the input is given to EMTP to get the peak values of overvoltages then calculate global risk of the network and the same data is used to train the ANN. Error is calculated by the difference of EMTP output and ANN output. This error issued to adjust the weight of connection [8].

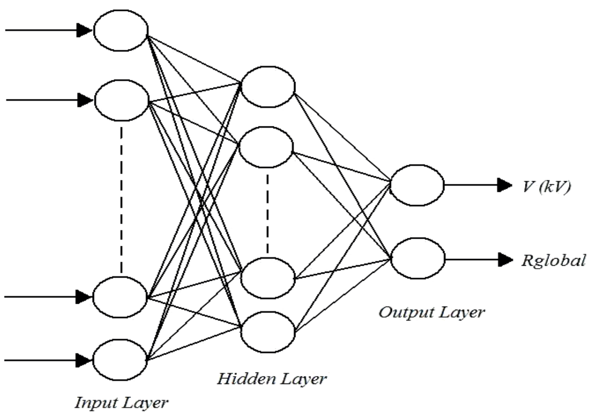

Fig. 1. Proposed MLP-based architecture.

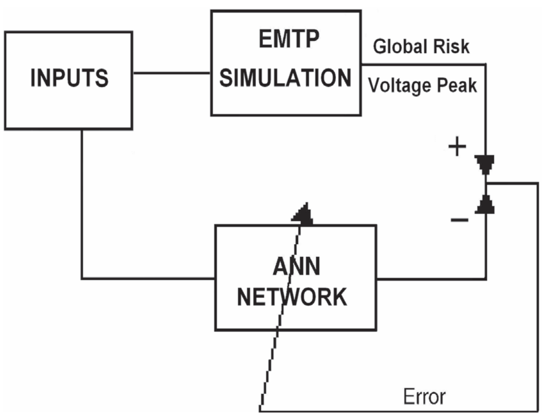

Fig. 2. Supervised learning of ANN.

4 OPTIMIZATION OF SURGE ARRESTERS' LOCATION IN THE NETWORK

The optimization method in this work is based on genetic algorithm (GA) to find the optimum location of arresters which provide minimum value of global risk of power network. Eqn. 6 is the goal function that should be minimized. GA 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. GA uses chromosomes composed of string-coded genotype. It simulates crossover and mutation like nature process to develop a powerful search capability [9]. Briefly principals of GA are as follows [10]:

a) Encoding: The chromosomes in the population are presented as strings of binary digits. This encoding has several advantages as simplicity of applying genetic operators. After this, chromosomes which have equal genes to the number of candidate nodes of network will be produced.

b) Evaluation: A chromosome should be evaluated to examine its fitness for being a solution. In fact chromosomes, which are proper or have better fitness are selected as parents or migration. The goal function in GA is neural net model of risk formula (6). Because of minimization nature of the problem, rank selection can be used to select the best individuals. After developing answers for the individuals produced by neural net, chromosomes sorted from worst to best and numbers in the range of 1 to the number of nodes attributed to each node as a fitness number. Then the roulette wheel can be used to select the chromosomes with proper probability [11]. The probability of selection *i*th chromosome is:

$$P_S(i) = \frac{fitness(i)}{\sum_{k=1}^{S} fitness(k)} \qquad (7)$$

where *fitness(i)* is fitness number attributed to *i*th chromosome and *S* is the total number of individuals in generation. Two chromosomes will be selected in each generation to produce offspring. One is the best individual and other elected randomly.

c) Crossover: Parents in each generation should have crossover to produce children. A single point crossover can be used. One point is selected randomly in parents string of genes, then first part of one parent is joined to the last part of the other one holding genes order and generates two offspring.

d) Mutation: 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 optimum position of arresters, there are two groups of individuals. 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 genes, mutation is used to avoid stopping algorithm in very good chromosomes and some of these individuals have mutation with changing one or two genes of their strings.

5 CASE STUDY

The optimization method described before has been applied to obtain the optimum positions of five arresters, which should locate on Iranian southeast 400 kV network, Fig. 3. The network composes of four 400 kV overhead lines and one power plant. Reactors, transformers and other substation components have been ignored and the other end of radial lines are assumed be open to consider the worst case of overvoltages. Also the substation arresters have been removed to test the algorithm for placing the arresters in the end of open lines and estimate the most severe switching overvoltages. The worst case of switching operation, energizing the line having trapped charge on it, has been considered. For each position of arresters, 400 switching operations are performed statistically using the statistic switch of EMTP/ATP draw. Each overhead line is divided into three equal parts, so there are 12 candidate nodes in the network. All network simulation and modeling guidelines are based on [12]. In all cases the positions of 5 arrester sets were changed. The rated voltage of arresters is 336 kV and their protective characteristics are shown in Table 1.

Fig.4 represents the empirical cumulative distribution function (CDF), normal assumed CDF and weibull assumed CDF for overvoltage in node 4, when arresters are located on nodes 2, 3, 5, 8, 11. There is not much difference between distributions, so weibull distribution was adopted to calculate the failure risk.

Table 1. ARRESTER CHARACTERISITCS

I (kA)	1	5	10	10	20	40
V (kV)	666	751	790	790	869	972

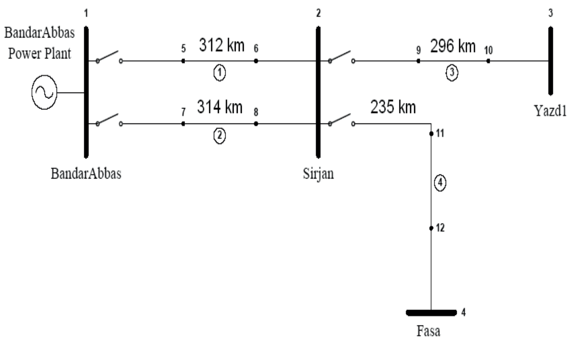

Fig. 3. Single diagram of case study.

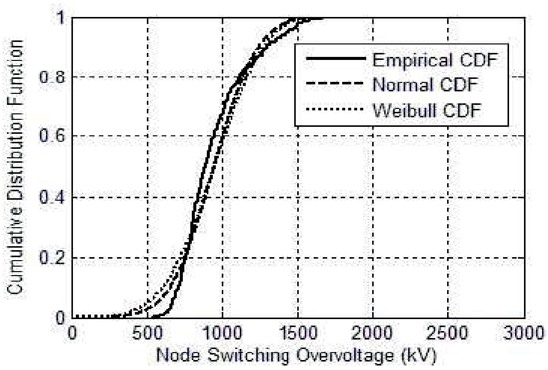

Fig. 4. Cumulative distribution of overvoltages.

The global risk of the network, eqn. (6), was calculated numerically for different position of arresters. The proposed method has been coded in Matlab v. 7.1 and all statistical calculations, ANN modeling and optimization procedure are calculated with this software. The program code runs the EMTP/ATP file, calls the results and evaluates the risk values directly. Totally 80 different position sets of arresters were simulated. Each position set consists of 5 candidate nodes for installation of arresters according to Appendix I.

For simplification voltage profile along the lines is assumed to be stepwise; then at all towers before one node the switching overvoltages are the same as the overvoltage at that node. Lines have been divided into three equal parts, so three-step voltage profile on each line is considered. However, with a flat assumed of voltage profile, switching flashover rate is much higher than the stepwise profile. Fig 5 presents global risk of the network for these two cases. Also Fig. 6 shows global risk of the network when BSL is 1050 kV or 950 kV. In this figure, the standard deviation i.e. *σ/CFO* is 5%.

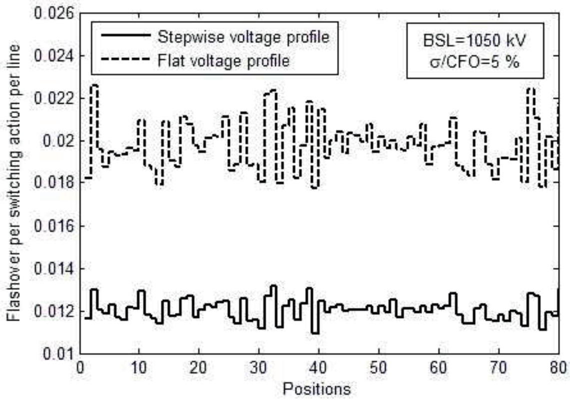

Fig. 5. Global risk of the netwrok for different position of arresters (According to appendix).

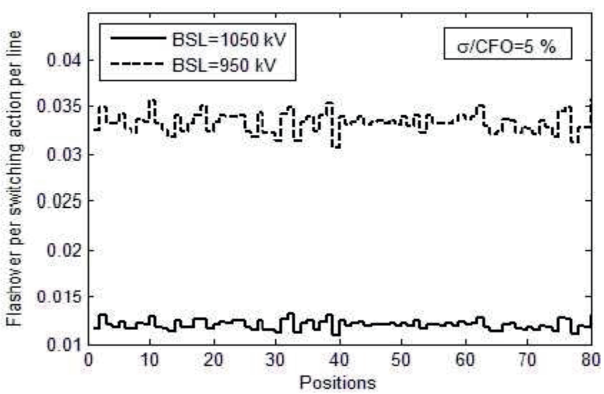

Fig. 6. Global risk of the netwrok for different position of arresters (According to appendix).

σ/CFO is per unit standard deviation which is considered 5% for tower insulation and 7% for station class insulation [13]. Fig. 7 shows the failure risk for these two values of standard deviation. From statistical data, 70 positions were selected to train the ANN. The mean square error of remaining 10 position sets that is predicted by ANN is 0.1%. Therefore, proposed ANN was qualified to be used in optimization process. A genetic algorithm with 45 initial population and 12 offsprings 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. 8.

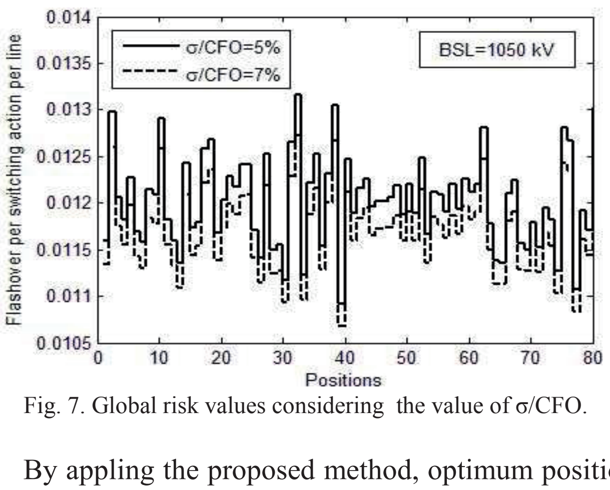

Fig. 7. Global risk values considering the value of σ/CFO.

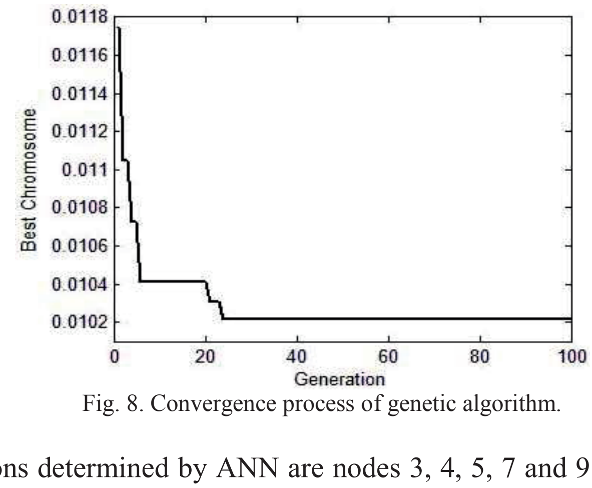

Fig. 8. Convergence process of genetic algorithm.

By appling the proposed method, optimum positions determined by ANN are nodes 3, 4, 5, 7 and 9 with predicted flashover rate per switching operation per line of 0.0102. Simulation by ATP with the same location of arresters (3, 4, 5, 7 and 9) gives the value of 0.0098. Therefore optimum position predicted by ANN will be acceptable for evaluation of minimum *SSFOR* in the network. Although all possible positions cannot be tested to verify the answer, but it is revealed that ANN model moves through optimum positions and determine a good answer in solution space, practically. 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 at desirable level and reduce global risk of failure of the network.

6 CONCLUSION

In this paper a simulation optimization based method was used to find the best position of five sets of arrester to set failure risk of the networks as less as possible. The proposed method consists of an ANN as a metal model and genetic algorithm as optimizer. The ANN results are investigated by simulation and after verifying the ANN model, genetic algorithm is used to find the optimum location of arresters that minimize global risk of the network. Selecting proper ANN Model and training process are very important to explore acceptable results. The proposed method was applied on Iranian southeast 400 kV network, where some nodes have to be selected for installation of arresters in order to satisfy a desired value of risk. The implemented algorithms optimize the surge arrester location, working with known risks of failure.

7 APPENDIX

In each position set, interesting nodes are those where arresters are installed. Network simulations were performed for each position set and relative failure risk was calculated. For example 10 position sets are presented in Table 2.

TABLE 2. DIFFERENT LOCATIONS FOR A SET OF 5 ARRESTERS

Pos. Set	Interesting Nodes	Pos. Set	Interesting Nodes
1	2, 5, 7, 10, 12	6	4, 8, 9, 10, 11
2	2, 3, 5, 8, 11	7	2, 6, 8, 10, 11
3	1, 4, 6, 9, 12	8	1, 4, 8, 11, 12
4	1, 3, 4, 6, 7	9	2, 3, 4, 6, 9
5	2, 3, 5, 8, 9	10	1, 5, 6, 10, 11

8 BIBLOGRAPHY

[1] IEC Standard 71-2: 1996, "Insulation Coordination, part 2: Application guide".

[2] K. Froehlich, C. Hoelzl, M. Stank and et all, "Controlled switching on shunt reactor compensated transmission lines Part I: closing control device development," IEEE Trans. Power Delivery, vol. 12, pp. 734-740, Apr. 1997.

[3] L. Stenstrom and M. Mobedjina, "Limitation of switching overvoltages by use of transmission line surge arresters", in Proc. 1998 CIGRE SC 33 International Conf., 1997.

[4] IEEE Std. 1313.2:1992, "IEEE Guide for the Application of Insulation Coordination".

[5] A. R. Hileman, "Insulation Coordination for Power Systems", Power Engineering Series, Marcel Dekker, Inc., New York (1999), p. 100.

[6] Electra 1973 No. 30, "Switching overvoltages in EHV and UHV systems with special reference to closing and reclosing transmission lines", Cigre Working Group 13-02.

[7] V. Leonardo Paucar, Marcos J. Rider, "Artificial neural network for solving the power flow problem in electric power system", Electr. Power Syst. Res. 62 (2002) 139–144.

[8] D. Thukaram, H.P. Khincha, and S. Khandelwal, " Estimation of switching transient peak overvoltages during transmission line energization using artificial neural network ", Intr. J. of Eelec. Power Syst. Research, Vol. 20 No. 3, July 2005.

[9] J. A. Miler et al., "An Evaluation of Local improvement Operators for Genetic Algorithms", IEEE Trans. Systems, Man and Cybernetics, 23, (1993) (5), pp. 1340-1351.

[10] L. Davis, "A Handbook of genetic Algorithms", Van Nostrand Reinhold, New York (1991).

[11] D. E. Goldberg, "Genetic Algorithm in Search, Optimization and Machine Learning", Addison –Wesley, Reading, MA (1989).

[12] A. I. Ibrahim, H. W. Dommel, "A Knowledge Base for Switching Surge Transients", Proc. of IPST 2005, Montreal, Canada.

[13] IEC Publication 71-1:1993, "Insulation Coordination Part I: Definitions, Principals and Rules".