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A new wavelet network based method to estimate the lightning-related risk of failure of power system apparatus

Navid Ghaffarzadeh *

Faculty of Engineering and Technology, Imam Khomeini International University, Qazvin, Iran

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ABSTRACT

This paper proposes a new and fast wavelet network based method for estimating the risk of failure caused by lightning overvoltages in arrester protected networks. First, failure risks obtained by simulations are used as the training data for training the wavelet network. The trained wavelet network is then used for accurate and fast estimating of the lightning-related risk of failure of power system apparatus for all possible conditions. The accuracy of the proposed method has been tested and verified under various conditions in the 230 kV network of Sistan–Baluchestan. Performance of the new method has also been compared with several existing methods under same conditions, and the test results show better accuracy of the proposed method. The proposed method not only does not have the restriction of conventional methods, but also it does not have the limitations associated with traditional neural networks based algorithms such as convergence to local optimum points, over-fit and/or under-fit problems. The main contribution of the paper is an accurate (due to proper selection of the training data set based on the *k*-fold cross validation technique and using wavelet network for estimation), fast (mean calculation time for the network risk of failure computation is 54 s) and simple wavelet network-based algorithm (as compared to the conventional algorithms) for estimating the lightning-related risk of failure of power system apparatus.

Introduction

Risk-based insulation coordination approaches has received significant attention in recent years [1–4]. This is especially true in the case of lightning stresses, which are the main cause of short duration and long duration power supply interruptions [5]. In the literature, several methods have been proposed and implemented for evaluation of the failure risk of the network as a result of the lightning strokes.

Refs. [1–3] present approaches based on the numerical integration technique for calculating the risk of the failure of the network as a result of the lightning strokes. In [4] the first order reliability method is suggested for evaluating the lightning-related risk of failure of the network. In [5], both of the numerical integration technique and the first order reliability method are utilized for determining the failure risk of the network. Also In this reference, these two methods for evaluating the lightning-related risk of failure has been compared. A Monte-Carlo scheme has also been carried out in some methods [6,7]. Statistical and probabilistic approaches to evaluate lightning failures have been introduced in [8,9], respectively.

As it will be mentioned in Section 'The proposed method', computing the lightning-related risk of failure of the network for all possible conditions of arresters by using conventional methods is very time consuming. So it is necessary to introduce an accurate and fast method to estimate the risk of failure in the network. In this paper a new and fast approach for estimating the risk of failure caused by lightning overvoltages in arrester protected networks has been proposed. This method is based on the wavelet network (WN). Since the failure risks which are used for training the WN are obtained by integrating the product of two probability density functions (i.e. overvoltage happening probability density function and probability distribution function of disruptive discharge of apparatus insulation against various voltages), the first step is to determine these two probability functions. After determining these functions, the risk of failure of each node is calculated. Then by using the risk functions of all nodes and considering the weighting factor for each node, the risk of failure of the network is obtained. In the next stage, by inserting the arresters in different positions and carrying out relevant simulations, the risks of failure of the network related to different situations are obtained and used as training data. Finally the trained WN is used to estimate the risk of failure of the network for unknown conditions. Obtained results show that the trained WN could estimate the network risk of failure in a precise manner.

* Tel.: +98 28 33901294.
E-mail address: ghaffarzadeh@eng.ikiu.ac.ir

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Risk of failure formulation

A risk of failure of a network component formulation had been proposed in [2] as follows:

$$R_f = \int_0^{\infty} f_v(u) \cdot F_d(u)du \tag{1}$$

where $f_v(u)$ is the probability density function of the lightning overvoltage happening and $F_d(u)$ is the probability distribution function of disruptive discharge of apparatus insulation (see Fig. 1).

It is generally assumed that the $f_v(u)$ is given by a log-normal distribution [10].

$$f_v(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma_{\ln x} \cdot x} e^{-\frac{1}{2}\left(\frac{\ln x - \ln \bar{x}}{\sigma_{\ln x}}\right)^2} \tag{2}$$

where $\sigma_{\ln x}$ is the standard deviation of $\ln x$, and $\bar{x}$ is the median value of x.

Also, the probability distribution function of disruptive discharge of apparatus insulation ($F_d(u)$) is defined as follows:

$$F_d(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma_{\ln x} \cdot x} \int_0^{x} e^{-\frac{1}{2}\left(\frac{\ln x - \ln CFO}{\sigma_{\ln x}}\right)^2} dx \tag{3}$$

where CFO is the Critical Flash Over voltage (i.e. voltage under which the insulation has a 50% probability to flashover or to withstand).

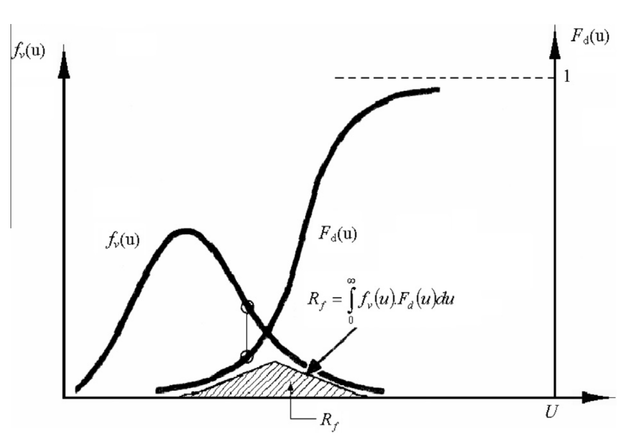

Fig. 1. The risk of failure of a network component.

Wavelet networks

Wavelet networks (WNs) combine the theory of wavelets and neural networks into one. WNs belong to the class of feed forward neural networks, with wavelets as the activation functions [11]. Unlike the feed forward neural networks, the structure of WNs can be obtained under the guidance of wavelet theory. WNs are based on the wavelet transform, orthonormal wavelet and wavelet frames as discussed in Appendix A.

Wavelet network structure

To approximate an arbitrarily nonlinear function, there are two processes in the WN algorithm: Network construction (e.g., using network structure to analyze the wavelet and updating its parameter to retain the network topology for further processing) and Error Minimization (e.g., minimization based on an adaptive Least Mean Square (LMS) algorithm and updating parameter of the network initialization using the steepest-descent gradient method) [11,12].

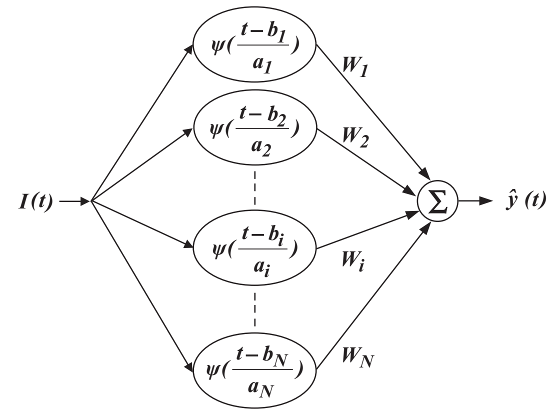

Fig. 2. Structure of a wavelet network.

The WN architecture approximates a signal $\hat{y}(t)$ with linear combination of a set of daughter wavelet (Eq. (A.2)) which is formed with dilation a and translation b of the mother wavelet. The approximate signal of the network $\hat{y}(t)$ can be written as

$$\hat{y}(t) = \sum_{i=1}^{N} I(t) \cdot w_i \cdot \psi\left(\frac{t - a_i}{b_i}\right) \tag{4}$$

where N is the number of wavelet and w_i is the weight coefficient. Fig. 2 depicts the structure of a WN.

At the sight of Eq. (4), the wavelet network is completely defined by the tuple (ψ, w_i). Its optimized components may be obtained by calculating the weights w_i and wavelet's number (N) that minimize the least mean square error function for $\hat{y}(t)$, i.e. the ones that make the model fit better to the original function $\hat{y}(t)$. This calculation hence implies finding the most suitable N wavelets on which to project, along with the weight that each component should to be given – how much it should to contribute to the overall description of $\hat{y}(t)$ – in order to maximize the approximation.

Determination of the number of wavelet (N), is an important task to reduce the problem of model order. To solve this problem, a part of the model data is used to approximate the model order. For this purpose, several approaches exist, such as cross-validation, generalized cross-validation, model complexity penalty, statistical hypothesis test, minimum description length criterion, Mallows criterion and Akaike Final Prediction Error (AFPE) [11].

In this paper, the AFPE approach is adopted and used to minimize the equation

$$J_{\mathrm{AFPE}}(\hat{f}_s) = \frac{n + N \cdot d_l + 2 \cdot N}{n - N \cdot d_l - 2 \cdot N} \cdot \frac{1}{2n} \sum_{j=1}^{n} \left(\hat{f}_s(I_j) - y_j\right)^2 \tag{5}$$

where $\hat{f}_s$ is the wavelet network, N is the number of wavelets in the network, d_l is input dimension and n is the number of training inputs.

It should be mentioned that the AFPF approach was selected due to the results obtained in Ref. [13]. The different approaches (cross-validation, generalized cross-validation, model complexity penalty, statistical hypothesis test, minimum description length criterion, Mallows criterion and Akaike Final Prediction Error (AFPE)) have been numerically tested for determining the number of wavelets in wavelet network in Ref. [13] and it turns out that the AFPE works quite well when tested on a variety of examples [13].

The wavelet network parameters w_i, b_i and a_i are optimized by using Least Mean Square (LMS) to minimize the cost as a function of energy at time t, with