NEURAL NETWORK BASED MONTE CARLO ANALYSIS FOR ESTIMATING THE LIGHTNING PERFORMANCE OF DISTRIBUTION LINES

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Abstract – **The evaluation of the lightning performance of overhead lines is generally based on a statistical calculation, due to the random nature of the lightning phenomenon. This task can be very long if sophisticated algorithms are used for calculating lightning overvoltages. The application of a neural network can shorten the flashover rate calculation. This paper summarizes the work made to analyze the lightning performance of overhead distribution lines using neural networks. The document includes a discussion on the advantages and limitations of the proposed approach.**

Keywords: Lightning Overvoltages, Electrogeometric Model, Statistical Analysis, Monte Carlo Method, Neural Networks.

I. INTRODUCTION

One of the main difficulties presented in the evaluation of the lightning performance of electric equipment is the lightning characterization, due to the random nature of this phenomenon. In addition, actual lightning data are scarce, and its random nature forces to carry out statistical analyses.

The Monte Carlo method is a widely used approach in statistical analysis of power system overvoltages. The application of this method to the statistical analysis of lightning overvoltages on overhead distribution lines is usually aimed at determining the lightning flashover rate. It can be a hard and long task if accurate and sophisticated algorithms are used for calculating lightning overvoltages.

In general, it is for the calculation of overvoltages induced by discharges to ground when the task can be very complex. An approximation based on a neural network could reduce this complexity and the calculation time.

The approach proposed in this paper can be summarized as follows. A sequence of lightning strokes is randomly generated; the overvoltage originated by each stroke on a distribution line is then calculated. This information is used to train a neural network, whose validation is performed by using a new sequence of lightning strokes. The following sections present a summary of the study addressed to obtain the lightning flashover rate of overhead distribution lines using a neural network.

II. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN), hereinafter also named as neural network, is a parallel distributed processor inspired by biological models [1] – [3]. ANNs can be used to solve problems that have proved to be difficult with conventional algorithms. The basic unit of an ANN is the neuron. A neuron model has a set of inputs that are weighted and combined between them to generate the total input, see Fig. 1. A transfer function determines the state of activation or the output signal of the neuron from the total input and the previous state of activation. The output signal is sent to other units of the network through unidirectional communication channels.

A neural network will be able to carry out a task by an adequate selection of the architecture, its processing units and the learning process. In general, the architecture may consists of three parts, the input layer, the output layer, and one or several hidden layers. The learning process allows neural networks to modify its weights in response to an input information. The changes produced during this process are reduced to destruction, modification and creation of connections between neurons; this process finishes when the values of the weights remain constant.

An important aspect is the selection of the criteria that must be followed to change the weights of the connections. These criteria determine what it is known as learning rule. In general, it is possible to consider two types of rules : supervised and non-supervised learning. The main difference between both types lies in the existence or not of an external agent (supervisor) that takes over the training process of the network. The most convenient learning rule for a specific neural network is intimately related to its architecture.

The aim of this work is to develop neural networks that could calculate the lightning flashover rate of overhead distribution lines. This goal will be achieved by using several algorithms to train the neural networks. At the end they should be capable of reproducing the same results that the original algorithms. To carry out this work a feedforward multilayer network based on the back-propagation model has been considered, see Fig. 2.

The backpropagation algorithm is based on an iterative process; during a training session two patterns, input and target, are presented to the network. The input pattern produce output patterns at each neuron of each layer. An

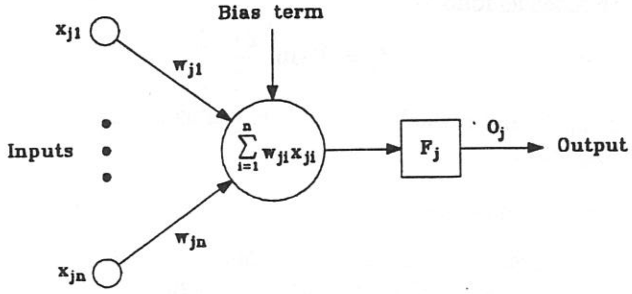


Fig. 1. Inputs and outputs of a neuron.

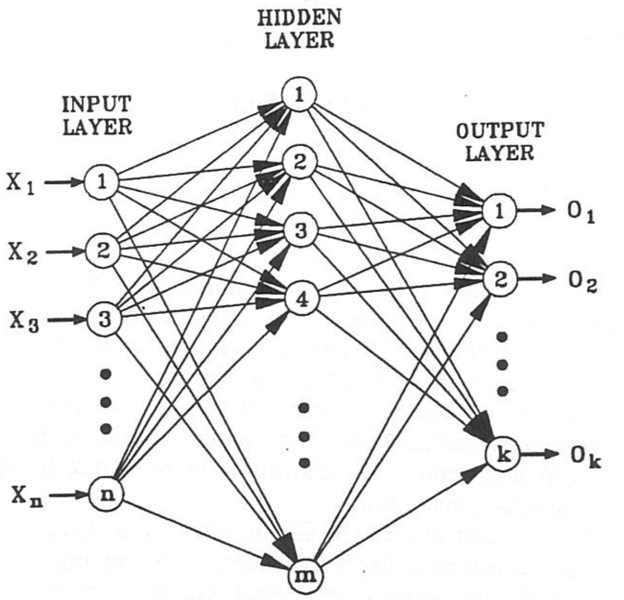


Fig.2. Feedforward multilayer architecture.

error signal is obtained from the difference between the calculated and the target outputs, the value of this error is minimized by adjusting the weights. The speed of this process will depend on several factors, such as the learning rule, the transfer function of neurons or the initialization of the network [1] - [3].

III. LIGHTNING OVERVOLTAGES ON OVERHEAD LINES

The calculation of the overvoltage originated by a stroke is based on a two-stage procedure. First, it is determined whether a discharge hits a line or ground, using the electrogeometric model [4]. Then the overvoltage is calculated using a different algorithm for each type of discharge. A summary of the algorithms used to calculate lightning overvoltages and train the neural network are presented in the subsequent sections.

3.1 Strokes to phase conductors

The maximum voltage originated by a stroke that hits a phase conductor can be approximated by the following expression

$$V = Z_c \cdot I/2 \tag{1}$$

where I is the peak current and Z_c the wave impedance of the conductor. The value of the wave impedance is obtained as follows

$$Z_c = 60 \cdot \ln\left(\frac{2\,h_c}{r_c}\right) \tag{2}$$

being h_c and r_c the height and the radius of the conductor, respectively.

3.2 Strokes to ground

Induced overvoltages in a phase conductor due to nearby strokes will be calculated using two different approaches.

a) Rusck's method

The maximum voltage induced in the point closest to the stroke is given by [5]

$$V = \frac{Z_0\, I\, h}{y}\left(1+\frac{1}{\sqrt{2}}\frac{v}{c}\frac{1}{\sqrt{1-\frac{1}{2}\left(\frac{v}{c}\right)^2}}\right) \tag{3}$$

where y is the closest distance between the stroke and the line, I is the peak current, h is the mean height of the conductor, v is the return stroke velocity, c is the velocity of light in free space, and $Z_0 = 30\ \Omega$.

Using this procedure, only the calculation of the overvoltage induced on the highest conductor is needed.

When the line is shielded the voltage induced in a phase conductor is computed by using a shielding factor or protective ratio

$$V' = pr \cdot V \tag{4}$$

being V the voltage induced when there is no shield wire, its value is computed according to (3).

If the shield wire is grounded to a resistance to ground R, the protective ratio is given by [7]

$$pr = 1 - \frac{h_{sw}}{h_c} \cdot \frac{Z_{sw\text{-}c}}{Z_{sw} + 2R} \tag{5}$$

where h_{sw} is the shield wire height, h_c is the phase conductor height, Z_{sw} is the wave impedance of the shield wire, and $Z_{sw\text{-}c}$ is the mutual impedance between the shield wire and the conductor. Both impedances are calculated as follows

$$Z_{sw} = 60 \ln\left(\frac{2\,h_{sw}}{r_{sw}}\right) \tag{6}$$

$$Z_{sw\text{-}c} = 60 \ln\left(\frac{D_{c\text{-}sw}}{d_{c\text{-}sw}}\right) \tag{7}$$

being r_{sw} the radius of the shield wire, $D_{c\text{-}sw}$ the distance between the conductor and the image of the shield wire, and $d_{c\text{-}sw}$ the distance between the conductor and the shield wire.

b) Chowdhuri's method

It is a more sophisticated method based on a multi-conductor representation of an overhead line. The voltage induced in the j-th conductor of a n-conductor line is obtained from an equation having the following form

$$V_j = V_{js} \cdot \left(M_j c^2\right) \tag{8}$$

where V_{js} is the voltage induced in the same conductor in the absence of the other conductors, M_j is a factor that depends on the geometrical configuration of the line, and c is the speed of light [6] - [8]. The above equation has been used to obtain the voltage induced by a rectangular return stroke function [8]. The induced voltage for any arbitrary waveshape of the return stroke can then be computed by applying the Duhamel's integral.

The same approach can be used to obtain voltages induced in a shielded line, by changing only the calculation of coefficients M_j [7].

3.3 Strokes to shield wires

The phase-to-ground voltage across the insulation of a tower is calculated from the following equation [5]

$$V = V_t \cdot (1 - CF) \tag{9}$$

being CF the coupling factor between the conductor and the shield wire, and V_t the tower top voltage. This voltage can be deduced from the following expression [5]

$$V_t = \frac{I}{2}\, t \cdot \left[Z_I - \frac{Z_W\left(1-\varphi^N\right)}{1-\varphi} \right] + I\, \tau\, Z_W \left[\frac{\left(1-\varphi^N\right)}{(1-\varphi)^2} - \frac{N\varphi^N}{1-\varphi} \right] \tag{10}$$

where

$$Z_W = \frac{2R_i^2 Z}{(Z+R_i)^2} \frac{(Z-R_n)}{(Z+R_n)} \tag{11}$$

$$Z_I = \frac{R_i Z}{(Z+R_i)} \tag{12}$$

$$\varphi = \frac{(Z-R_i)\,(Z-R_n)}{(Z+R_i)\,(Z+R_n)} \tag{13}$$

being I the peak current of the return stroke, R_i the ground resistance of the pole struck, R_n the ground resistance of the adjacent pole, τ the travel time along the span, $N = t/2\tau$ the largest value that the wave number can reach, and $Z = Z_{sw}/2$. This equation is solved at $t = 2\ \mu s$ [5].

The coupling factor is calculated as follows

$$CF = \frac{Z_{sw-c}}{Z_{sw}} \tag{14}$$

IV. LIGHTNING PARAMETERS

It is generally assumed that the probability density function of a lightning variable is given by a log-normal distribution [9]

$$p(x) = \frac{1}{\sigma_{\ln x}\, x \sqrt{2\pi}} \cdot \exp\left\{ -\frac{1}{2} \left(\frac{\ln x - \ln \bar{x}}{\sigma_{\ln x}} \right)^2 \right\} \tag{15}$$

being $\bar{x}$ and $\sigma_{\ln x}$ the mean value and the standard deviation of the logarithm of the variable. When two variables are involved, this function has the following form

$$p(x,y) = p(x) \cdot p(y) \frac{\exp\left\{ -\rho \left(\frac{\ln x/\bar{x} \cdot \ln y/\bar{y}}{\sigma_{\ln x}\, \sigma_{\ln y}} \right) \right\}}{\sqrt{1-\rho^2}} \tag{16}$$

where ρ is the coefficient of correlation. If the variables are assumed independently distributed then $\rho = 0$, and

$$p(x,y) = p(x) \cdot p(y) \tag{17}$$

These functions are related to the first stroke, which usually presents the highest peak value.

The cumulative probability of the current peak, I, exceeding a given value, i_0, is derived from p(I), and approximated by the following equation [5]

$$P(I \geq i_0) = \frac{1}{1 + (i_0/31)^{2.6}} \tag{18}$$

Overvoltages induced by nearby strokes to ground can be a serious problem for lines with low insulation levels, being the magnitude of these overvoltages a function of the velocity of return strokes. Therefore the velocity is another significant parameter to be included in the study. However, experimental data for the return stroke velocity are scarce. In addition, this parameter may have a geographical dependence, and the characteristics of triggered lightning may be different from those of natural lightning [10].

A relationship between the current and the velocity of the return stroke has been proposed with the following general form

$$v = \frac{c}{\sqrt{1 + \frac{W}{I}}} \tag{19}$$

where v is the velocity of the return stroke, W is a constant, and I is the peak current. This expression can be used to obtain the so-called striking distance that is the basis of the electrogeometric model [4].

V. ANN APPLICATION TO THE CALCULATION OF LIGHTNING OVERVOLTAGES

5.1 Introduction

The goal is to develop a neural network architecture that could calculate the voltages originated by each type of discharge. Although two different algorithms have been used for the calculation of induced overvoltages during the learning process, the information to be produced by all neural networks is the same, that is the output pattern has two values: the type of stroke for unshielded lines (direct to a phase, indirect) or for shielded lines (direct to a phase, direct to a shield wire, indirect), and the lightning overvoltage.

As for the input patterns, it is obvious that they depend on the overvoltage calculation algorithm, but three types of variables can be distinguished in all the cases : lightning stroke characteristics, stroke location, and line geometry. The following input variables were chosen in this work

- the peak current, the return stroke velocity, the closest distance from the stroke to the line, and the height of the line, when the Rusck's algorithm is used with unshielded lines
- the peak current, the time to crest, the return stroke velocity, the closest distance from the stroke to the line, the distances between conductors and the height of each conductor, when the Chowdhuri's method is used with unshielded lines
- the peak current, the return stroke velocity, the closest distance from the stroke to the line, the distances between conductors, the height of each conductor, the height of the shield wire, and the ground resistance, when the Rusck's method is used with shielded lines
- the peak current, the time to crest, the return stroke velocity, the closest distance from the stroke to the line, the distances between conductors, the height of each conductor, the height of the shield wire, and the ground resistance, when the Chowdhuri's method is used with shielded lines.

Although phase conductor and shield wire radii are parameters involved in overvoltage calculations, they were not included in any input pattern, and all neural networks were trained using the same values, $r_c = 5$ mm and $r_{sw} = 2.5$ mm, for all distribution lines. In addition, the height of the cloud charge center was kept constant, $h_c = 3$ km, when the Chowdhuri's method was used.

5.2 Unshielded lines

Initially, it was decided to consider an architecture with at least one hidden layer, use tan-sigmoidal transfer functions for the hidden layers, lineal transfer functions for the output layer, and only the Rusck's algorithm for training. The input patterns were generated by assuming that

- the peak value and the time to crest of a lightning stroke had a joint probability density function according to (16), with $\rho = 0$
- the return-stroke velocity had a uniform distribution, ranging between 30000 and 150000 km/s
- the probability density function of the distance from the stroke location to the line had a uniform distribution and varied between 0 and 500 m.

Five different heights of the line (5, 8, 11, 14 and 17 m) were considered. Because of the great differences between overvoltages originated by direct and indirect strokes, all calculations were performed with normalized input and output patterns. 500 input patterns per height were randomly generated. After some adjustments the errors obtained by the stroke classifier and the overvoltage calculator were smaller than 1% and 2% respectively. The architecture of the neural network was that shown in Fig. 3, it has two hidden layers with 14 and 12 neurons respectively.

The same architecture was later trained using the Chowdhuri's method and 2800 input patterns generated in a similar way. This architecture did prove to be again acceptable, being errors obtained with the stroke classifier and the overvoltage calculator smaller than 1% and 2% respectively.

5.3 Shielded lines

The architecture developed during the training of

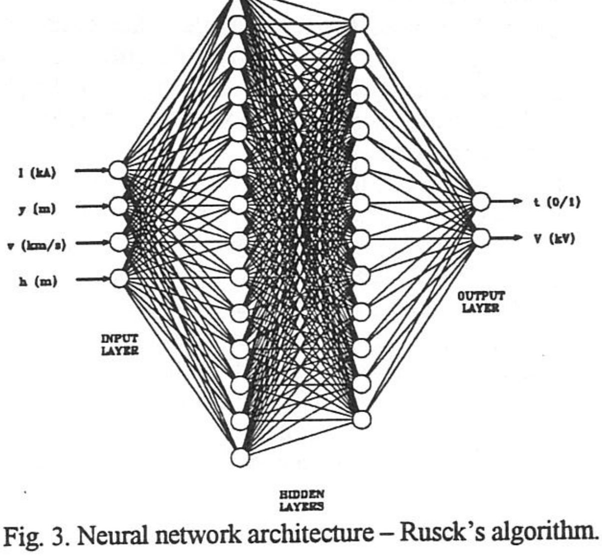


Fig. 3. Neural network architecture – Rusck's algorithm.

unshielded lines was also used for shielded lines. However, two additional input patterns were added,

- the ground resistance, for which three constant values were used with each line configuration, 10 Ω, 40 Ω and 70 Ω
- the height of the shield wire, for which two different values were used with each line configuration.

The architecture of the neural network was trained using 8640 input patterns with both methods. Its performance was acceptable again, being errors obtained by the stroke classifier and the overvoltage calculator smaller than 5% with both methods.

VI. STATISTICAL ANALYSIS

The neural network architectures were validated by performing statistical analysis, whose results were compared to those deduced by using the original training algorithms; the most important results are summarized in this section.

Up to 5000 events were randomly created by assuming that the point of impact was uniformly distributed, while the joint probability density function of the current peak and the time to crest of each stroke was that presented in (17). As for the velocity of the return strokes two alternatives were considered

- velocities were uniformly distributed, ranging from 30000 to 150000 km/s
- velocities were related to the maximum currents of the strokes according to (19), assuming that the value of the coefficient W was ranging from 50 to 500.

Tables I and II show the flashover rates calculated using both the original algorithms and the neural networks, and assuming uniformly distributed return stroke velocities [11]. All calculations were performed by ignoring the power frequency voltage. Flashovers originated by different types of discharges are presented separately, so it is possible to distinguish the performance of the neural networks very easily. It is evident that the differences between values obtained from algorithms and neural networks are very small for direct strokes or backflashovers, and in general the total error can be acceptable.

A very different performance was observed when the velocity of a stroke is deduced from its maximum current and using the neural networks trained assuming a uniform distribution of this velocity. In this case, the differences were very significant for some values of W. This performance can be justified by observing the resulting distribution of velocities for each coefficient W, as shown in Fig. 4. Only when velocities were ranging between 30000 and 150000 km/s, results obtained from the neural networks did match those from the algorithms, showing in this way the importance of the patterns used during the training process. For this reason, the neural networks were trained again, using the same architecture but considering this time the return stroke velocity as a function of the peak current. The new results are presented in Table III. The flashover rates were calculated by generating 5000 events for all test cases. Although the errors are still large for some cases, they are smaller than those obtained with the original neural networks.

Table I – Statistical analysis – Uniform distribution of the return stroke velocity with unshielded lines

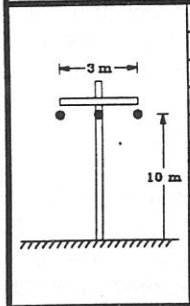
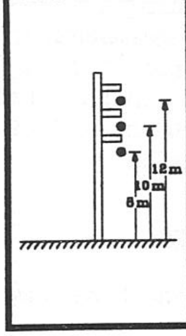
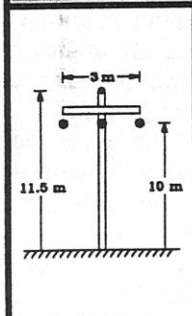
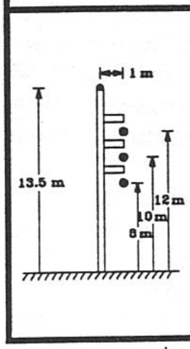
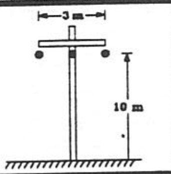
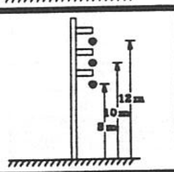
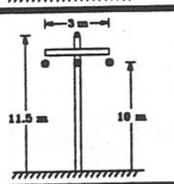
Line	Number of cases	NFO (fl/100km/yr) Direct	Indirect	Total	Direct	Indirect	Total
		Algorithm			Neural network		
		Rusck's Method					
	1000	10.60	1.40	12.00	11.10	1.50	12.60
	2000	10.65	1.30	11.95	10.85	1.80	12.65
	3000	10.96	1.16	12.13	11.13	1.60	12.73
	4000	11.35	1.32	12.67	11.35	1.67	13.02
	5000	11.40	1.34	12.74	11.30	1.60	12.90
		Chowdhuri's Method					
	1000	10.60	13.10	23.70	10.80	16.60	27.40
	2000	10.65	12.80	23.45	10.85	16.35	27.20
	3000	10.96	12.63	23.60	11.06	16.33	27.40
	4000	11.35	12.10	23.45	11.45	15.47	26.92
	5000	11.40	11.92	23.32	11.50	15.14	26.64
		Rusck's Method					
	1000	10.90	3.20	14.10	11.40	2.00	13.40
	2000	10.85	3.45	14.30	11.35	2.15	13.50
	3000	11.13	3.13	14.26	11.60	2.03	13.63
	4000	11.55	3.32	14.87	11.90	2.02	13.92
	5000	11.60	3.28	14.88	11.76	2.00	13.76
		Chowdhuri's Method					
	1000	10.90	14.90	25.80	11.20	16.00	27.20
	2000	10.85	14.65	25.50	11.35	15.85	27.20
	3000	11.13	14.56	25.70	11.46	16.43	27.90
	4000	11.55	13.97	25.52	11.75	16.22	27.97
	5000	11.60	13.74	25.34	11.76	16.08	27.84

Table II – Statistical analysis – Uniform distribution of the return stroke velocity with shielded lines

Line	Number of cases	NFO (fl/100km/yr) Direct	Backflash	Indirect	Total	Direct	Backflash	Indirect	Total
		Algorithm				Neural network			
		Rusck's Method							
	1000	0.00	8.60	0.20	8.80	0.00	7.50	1.40	8.90
	2000	0.00	9.00	0.15	9.15	0.00	8.05	1.10	9.15
	3000	0.00	9.43	0.13	9.56	0.00	8.50	0.96	9.46
	4000	0.00	9.77	0.10	9.87	0.00	8.90	0.97	9.87
	5000	0.00	9.90	0.10	10.00	0.00	9.00	0.92	9.92
		Chowdhuri's Method							
	1000	0.00	8.60	6.90	15.50	0.00	9.00	5.60	14.60
	2000	0.00	9.00	6.90	15.90	0.00	9.55	5.85	15.40
	3000	0.00	9.43	6.96	16.40	0.00	9.93	5.90	15.83
	4000	0.00	9.77	6.82	16.60	0.00	10.15	5.82	15.97
	5000	0.00	9.90	6.86	16.76	0.00	10.26	5.86	16.12
		Rusck's Method							
	1000	0.00	9.70	0.70	10.40	0.00	8.30	2.00	10.30
	2000	0.00	10.20	0.60	10.80	0.00	8.85	2.10	10.95
	3000	0.00	10.56	0.53	11.10	0.00	9.30	1.83	11.13
	4000	0.00	10.90	0.50	11.40	0.00	9.62	1.82	11.45
	5000	0.00	10.94	0.46	11.40	0.00	9.72	1.80	11.52
		Chowdhuri's Method							
	1000	0.00	9.70	7.60	17.30	0.00	9.60	7.20	16.80
	2000	0.00	10.20	7.30	17.50	0.00	10.10	7.25	17.35
	3000	0.00	10.56	7.40	17.96	0.00	10.53	7.23	17.76
	4000	0.00	10.90	7.35	18.25	0.00	10.80	7.20	18.00
	5000	0.00	10.94	7.42	18.36	0.00	10.90	7.34	18.24

ϕ_{ph} = 10 mm (phase conductor diameter) ; ϕ_{sw} = 5 mm (shield wire diameter) ; R = 50 Ω (ground resistance);
NFO = Number of FlashOvers ; CFO (Critical FlashOver voltage) = 150 kV ; N_g = 1 fl/km^2/yr (ground flash density)

Table III – Return stroke velocity as a function of the peak current

Line	W	Error (%) Rusck's Method	Chowdhuri's Method
	50	17.62	4.56
	200	6.74	2.20
	350	2.84	3.29
	500	7.33	11.27
	50	27.03	7.58
	200	14.09	17.07
	350	7.96	11.26
	500	1.07	5.16
	50	6.53	5.45
	200	5.20	5.44
	350	4.88	0.76
	500	15.24	16.95
	50	20.75	3.47
	200	12.00	1.82
	350	9.40	4.63
	500	5.36	13.53

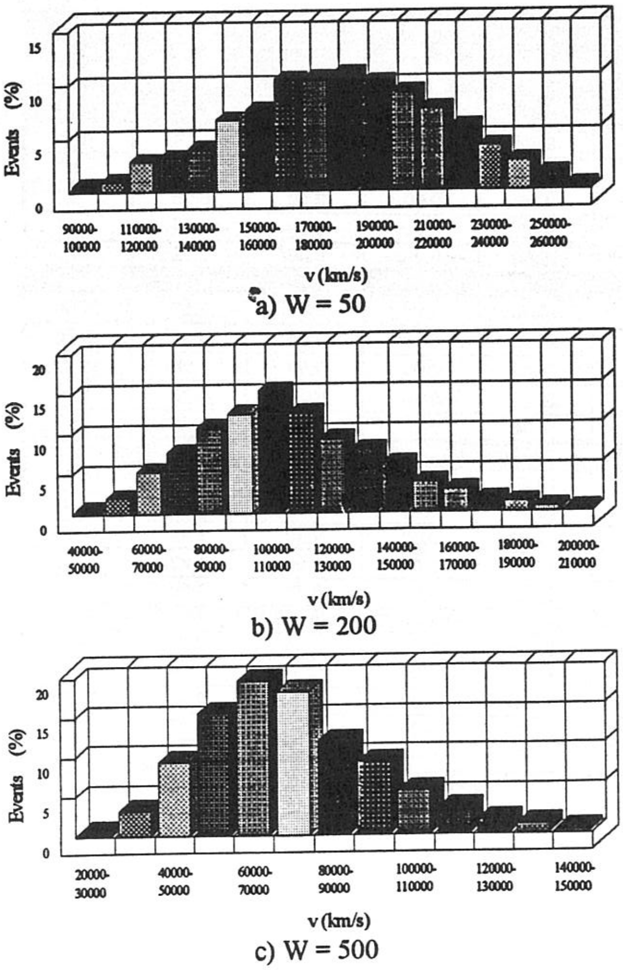


Fig. 4. Probability density of the return stroke velocity.

VII. CONCLUSIONS

This work has presented the application of ANNs to the lightning performance analysis of overhead distribution lines. From the validation of the neural networks one can conclude that it is possible to obtain a neural network architecture to differentiate between the types of discharges, and to calculate lightning overvoltages. The work has also proved the importance of the training process. The performance of a neural network was acceptable only when the validation was based on the same range of values used during the learning process.

The advantages of this approach are questionable if the algorithms used for training the neural network are simple. But even with sophisticated algorithms, the advantages are doubtful since the time needed to perform a statistical analysis can be rather short. The advantages are obvious when the training is based on actual measurements. The neural network model is another important aspect. The backpropagation algorithm has been widely used in many applications [3], but it has serious limitations, and it is not very adequate for real-time applications [2].

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