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**DETERMINATION OF THE CORONA MODEL PARAMETERS WITH  
ARTIFICIAL NEURAL NETWORKS**

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The aim of this study is to calculate new model parameters taking into account the corona of electrical transmission line wires. For this purpose, a neural network modeling proposed for the corona frequent characteristics modeling. Then this model was compared with the other model developed of Institute of Saint Petersburg Polytechnic. The results of development of the specified corona model for calculation of its influence on the wave processes in multi-wires line and determination of its parameters are submitted. Results of obtained calculation equations are brought for Electrical Transmission Line with allowance for superficial effect in the ground and wires with reference to developed corona model.

**1. INTRODUCTION**

The corona is not to want for cause of bad effect on electrical transmission line (ETL) and electromagnetic transient except some special applications. There are various models for the corona frequent characteristics [1-4]. One of the best models is combined model developed by Institute of Saint Petersburg Polytechnic [5-6]. In this developed method consists in components of resistance and capacitors (r and C). At first, the parameters  $r_1 - r_3$ ,  $C_1 - C_3$  are determined using the corona model consisting the three parallel branches r, C, without an additional connected element g which is necessary at capacities discharging during the time from corona extinction up to it next ignition. Further, by replacing one branch (such as branch  $r_3$ ,  $C_3$  into two or three branches r, C) the parameters of new elements determined. This process proceeds until necessary number of branches of the frequent characteristics ensuring concurrence of model and simulated object will be obtained. After determination of branches number and parameters of model the element g is connected to it. The value of element g is determined by a variation method. This developed method passed an evaluation test at modeling of superficial effect in the ground and wires was used for increasing of accuracy of the corona frequent characteristics modeling.

$$G = 0,83 \left( \frac{f}{50} \right)^{0,62} \left[ 1 - e^{-3,05 \left( \frac{U_M}{U_H} - 1 \right)} \right], \frac{1}{\text{M}\Omega \cdot \text{km}};$$

$$C = 2,4 \left( \frac{50}{f} \right)^{0,42} \left( \frac{U_M}{U_H} - 1 \right) \cdot 10^3, \frac{\text{pF}}{\text{km}} \quad (1)$$

Where, G and C are the additional conductivity and capacity of a line at certain frequencies and voltage; f is the frequency, Hz;  $U_M/U_H$  is the over voltage ratio. By using of the given formula for calculation of wave processes in a required range of frequencies, it is possible to calculate the necessary corona parameters for a line. At creating of model taking into account the wires corona one of the basic conditions is agreement of total conductivity and capacity of model in a certain frequent range with conductivity and capacity obtained from (1). Such conformity is possible to express by the following formula (according to model Fig. 1):

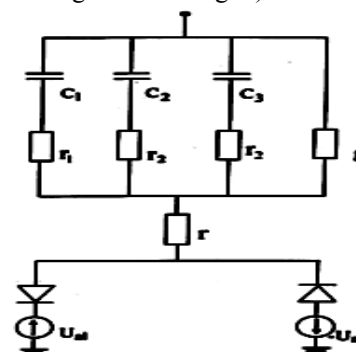


Fig.1 Three Angle Model

**2. DETERMINATION OF MODEL  
PARAMETERS OF THE CORONA OF ETL  
WIRES**

For determination of parameters characterizing the real ETL corona the various formulas are offered. Below the most frequently used formula [1][2] is brought:

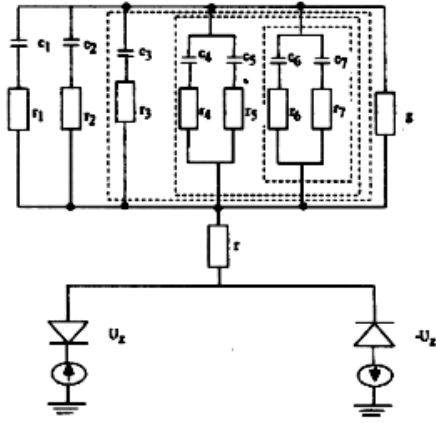


Fig.2. Seven Angle Model

$$j\omega_v c_1 + \sum_{k=2}^3 \left( r_k + \frac{1}{j\omega_v c_k} \right)^{-1} + g = G(\omega_v) + j\omega_v C(\omega_v) \quad (2)$$

Where,  $c_1, c_k, r_k, g$  are parameters of model;  $G(\omega_v), C(\omega_v)$  are parameters of a line at certain frequency. For determination of model parameters earlier in Institute of Physics the various formulas were obtained and error of model [7] is appreciated. At expansion of modeling range of over-voltage ratio increasing of parallel branches number caused to impossibility of parameters determination. The choice of additional elements' parameters by a variation method requires the large expenses of time, and in some cases becomes impossible.

## 2.1. PARAMETERS OF THE LINE AND THREE ANGLE MODEL

The parameters of initial model are determined from the decision of the equation:

$$\sum_{K=1}^3 \left( r_K + \frac{1}{j\omega_v C_K} \right)^{-1} = G(\omega_v) + j\omega_v C(\omega_v) \quad (3)$$

Where  $G(\omega_v), C(\omega_v)$  are parameters of ETL at  $\omega_v$  ( $v=1, 2, 3$ ) for certain meaning of  $U/U_3$ . From the formula (3) we shall obtain:

$$\begin{aligned} & -[C_1(\chi_2 + \chi_3) + C_2(\chi_1 + \chi_3) + C_3(\chi_1 + \chi_2)] = \\ & = \omega_v^2 G(\omega_v) - G(\omega_v)y_2 + C(\omega_v)y_1 + \omega_v^2 C(\omega_v)y_3 \\ & C_1 + C_2 + C_3 - \omega_v^2 [C_1\chi_2\chi_3 + C_2\chi_1\chi_2 + C_3\chi_1\chi_2] = \\ & = G(\omega_v)y_1 - \omega_v^2 G(\omega_v)y_3 + C(\omega_v) - \omega_v^2 C(\omega_v)y_3 \end{aligned} \quad (4)$$

Where,  
 $C_1 r_1 = \chi_1, \quad C_2 r_2 = \chi_2, \quad C_3 r_3 = \chi_3,$   
 $y_1 = \chi_1 + \chi_2 + \chi_3, \quad y_2 = \chi_1\chi_2 + \chi_1\chi_3 + \chi_2\chi_3, \quad y_3 = \chi_1\chi_2\chi_3.$

From system (4) after its transformation the following equations are received

$$\begin{vmatrix} A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \\ D_1 & D_2 & D_3 \end{vmatrix} \begin{vmatrix} y_1 \\ y_2 \\ y_3 \end{vmatrix} = \begin{vmatrix} A_0 \\ B_0 \\ D_0 \end{vmatrix} \quad (5)$$

Where

$$\begin{aligned} A_1 &= C(\omega_3) - C(\omega_1); A_2 = G(\omega_3) - G(\omega_1); A_3 = \omega_3^2 C(\omega_3) - \omega_1^2 C(\omega_1); \\ B_1 &= c(\omega_3) - c(\omega_1); \\ B_2 &= G(\omega_3) - G(\omega_2); B_3 = \omega_3^2 c(\omega_3) - \omega_2^2 c(\omega_2) \\ D_1 &= \sigma_2 [G(\omega_2) - G(\omega_3)] - \sigma_1 [G(\omega_1) - G(\omega_3)]; \\ \sigma_1 &= (\omega_3^2 - \omega_1^2)^{-1}; \\ D_2 &= \sigma_1 [\omega_3^2 C(\omega_3) - \omega_1^2 C(\omega_1)] - \sigma_1 [\omega_3^2 C(\omega_3) - \omega_1^2 C(\omega_1)]; \\ D_3 &= \sigma_2 [\omega_3^2 G(\omega_3) - \omega_2^2 G(\omega_2)] - \sigma_1 [\omega_3^2 G(\omega_3) - \omega_1^2 G(\omega_1)]; \\ A_0 &= \omega_3^{-2} G(\omega_3) - \omega_1^{-2} G(\omega_1); \\ B_0 &= \omega_3^{-2} c(\omega_3) - \omega_2^{-2} c(\omega_2); \\ D_0 &= \sigma_1 [C(\omega_1) - C(\omega_3)] - \sigma_2 [C(\omega_2) - C(\omega_3)]; \\ \sigma_2 &= (\omega_3^2 - \omega_2^2)^{-1} \end{aligned}$$

After determination of  $y_1, y_2$  and  $y_3$  by means of equation  $x^3 - y_1 x^2 + y_2 x - y_3 = 0$  the parameters of corona model are calculated. Then, for obtaining of a modeling error in a given range of frequencies, the frequent characteristic of the model is calculated at given over-voltage ratio:

$$G_M + j\omega_v C_M = \sum_{k=1}^3 \left( r_k + \frac{1}{j\omega_v c_k} \right)^{-1} \quad (6)$$

Where,  $G_M, C_M$  are total conductivity and capacity of corona model. At last the modeling error is calculated:

$$\begin{aligned} \Delta G &= \frac{G(\omega_v) - G_M}{G(\omega_v)} \cdot 100\%; \\ \Delta C &= \frac{C(\omega_v) - C_M}{C(\omega_v)} \cdot 100\% \end{aligned} \quad (7)$$

Calculated values of corona model's parameters for  $U_M/U_H=1,8$  are brought in Table 1. These obtained values can be accepted as base parameters. However, spent experiments have shown that if to accept the over-voltage ratio as instant meanings this base value should be specified in particular cases. If the third branch of corona model to replace by two branches  $r, c$  we receive the model whose parameters can be determined by decision of the equation:

$$\sum_{K=1}^3 \left( r_{K+2} + \frac{1}{j\omega_v C_{K+2}} \right)^{-1} = G(\omega_v) + j\omega_v C(\omega_v) - \sum_{K=1}^2 \left( r_K + \frac{1}{j\omega_v C_K} \right)^{-1} \quad (8)$$

## 2.2. PARAMETERS OF THE LINE AND SEVEN ANGLE MODEL

By using the sequential increase of corona model branches number it is possible to receive the model consisting of seven branches,  $r, C$ , Fig.2. Thus the parameters are determined under the similar formulas (4) - (5) obtained by decision of the following equation:

$$\begin{aligned} \sum_{k=1}^3 \left( r_{k+4} + \frac{1}{j\omega_v C_{k+4}} \right)^{-1} &= G(\omega_v) + \\ &+ j\omega_v C(\omega_v) - \sum_{k=1}^4 \left( r_k + \frac{1}{j\omega_v C_k} \right)^{-1} \end{aligned} \quad (9)$$

Calculated values of corona model's parameters (at  $U_M/U_H=1,8$ ) are brought in Table 2. The frequency dependences of conductivity ( $G$ ), capacity ( $C$ ) and

modeling error are brought. Here also the values of conductivity and capacity calculated by the formula (1) are brought for comparison. Thus models having high

accuracy are obtained, which can be successfully applied at numerical calculations of electromagnetic processes in multi-wires lines at certain regimes.

Table 1. Parameters of the line and three angle model

f	initial parameters		Parameters of the corona model					
Hz	1 $G( \overline{MOhm km} )$	C(pF/km)	r <sub>1</sub>	r <sub>2</sub>	r <sub>3</sub>	c <sub>1</sub>	c <sub>2</sub>	c <sub>3</sub>
50	0,758	1920	MOhm· km			pF/km		
200	1,497	1072,6	1,09	2,52	0,145	4620	-663	1130
1000	4,854	545,59						

Table 2. Parameters of the line and seven angle model

f	initial parameters		Parameters of the corona model													
Hz	1 $G( \overline{MOhm km} )$	C (pF/km)	r <sub>1</sub>	r <sub>2</sub>	r <sub>3</sub>	r <sub>4</sub>	r <sub>5</sub>	r <sub>6</sub>	r <sub>7</sub>	c <sub>1</sub>	c <sub>2</sub>	c <sub>3</sub>	c <sub>4</sub>	c <sub>5</sub>	c <sub>6</sub>	c <sub>7</sub>
2000	7.46	407.78	MOhm· km							pF/km						
2500	8.567	371.31														
3000	9.59	343.94	1,09	2,5	0,33	0,71	0,193	0,42	0,05	4620	-663	812	-209	1130	-250	398

### 3. DETERMINATION OF MODEL PARAMETERS BY NEURAL NETWORKS

Artificial neural networks (ANN) are physical cellular systems which can acquire, store and utilize knowledge. Currently neural networks can already be of great value in helping to solve many problems. Architectures with a large number of processing units enhanced by extensive interconnectivity provide for concurrent processing as well as parallel distributed information storage. In this study, a multi-layer, feed-forward, back-propagation ANN architecture is used. The input vector representing the pattern to be computed is incident on the input layer and is distributed to subsequent hidden layer, and finally to the output layer via weighted connections. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a nonlinear activation function (transfer function). ANN makes the recognition too slow and lacks the capacity of the computation. Second is the fully connected mesh structure of the system. It makes no chance of dealing with the order of the input variables. Although the order can be presented in various forms this make no sense to the output. The last is local affects of neighbors are ignored at the output layer. In other words, local correlation's affecting the output is lost at the training phase of learning [8].

$$O_j = f(\text{net}_j), \text{net}_j = \sum_i w_{ji} O_i + \theta_j \quad (10)$$

$f(\text{net}_j) = \text{ATanh}(\text{net}_j)$  or  $f(\text{net}_j) = \text{sigmoid}(\text{net}_j)$  (11) where, the  $O_j$  implements the new value at the corresponding point. Multi-layered feed-forward network (MLP) has a better ability to learn the correspondence between input patterns and teaching values from many

sample data by the error back-propagation algorithm. Therefore, in this work we used feed-forward neural network and trained it by error back-propagation. Learning process uses the back propagation learning rules like in the previous layers. The simplest output loss function that can be used with the above network is the maximum likelihood estimation.

$$E_p = \frac{1}{2} \left[ \sum_{j \in \text{output}} (t_{pj} - o_{pj})^2 \right] \quad (12)$$

where, the set of m-dimensional input patterns;  $\{i_p = (i_{p1}, i_{p2}, \dots, i_{pm})\}; p \in P$  where P denotes set of presented patterns, and their corresponding desired n-dimensional output patterns (supervised output patterns)  $\{t_p = (t_{p1}, t_{p2}, \dots, t_{pn})\}; p \in P$  are provided, the neural network is trained to output ideal patterns as follows. The squared error function  $E_p$  for a pattern p is defined by (3).  $t_{pj}$ : target (desired) value,  $o_{pj}$ : actual network output value. The purpose is to make  $E = \sum_p E_p$  small enough by choosing appropriate  $w_{ji}$  and  $\theta_j$ . To realize this purpose, a pattern  $p \in P$  is chosen successively and randomly, and then  $w_{ji}$  and  $\theta_j$  are changed by

$$\Delta_p w_{ji} = -\varepsilon (\partial E_p / \partial w_{ji}) \quad (13)$$

$$\Delta_p \theta_j = -\varepsilon (\partial E_p / \partial \theta_j) \quad (14)$$

Where,  $\varepsilon$  is a small positive coefficient. By calculating the right hand side of (13) and (14), it follows that

$$\Delta_p w_{ji} = \varepsilon \delta_{pj} O_{p1} \quad (15)$$

$$\Delta_p \theta_j = \varepsilon \delta_{pj} \quad (16)$$

where;

$$\delta_{pj} = \begin{cases} f'(net_j)(t_{pj} - O_{pj}) \\ f'(net_j) \sum_k w_{kj} \delta_{pk} \end{cases} \quad (17)$$

Note that k in the above summation represents every unit k in the layer following the layer of j (unit j). In order to accelerate the computation, the momentum terms are added in (15-16),

$$\Delta_p w_{ji}(n+1) = \varepsilon \delta_{pj} O_{pi} + \alpha \Delta_p w_{ji}(n) \quad (18)$$

$$\Delta_p \theta_j(n+1) = \varepsilon \delta_{pj} + \alpha \Delta_p \theta_j(n) \quad (19)$$

where, n represents the number of learning cycles, and  $\alpha$  is a small positive value. In this study, the momentum and learning rate values are taken as 0.95 and 0.75, respectively. These values are found by trial and error. A back-propagation algorithm is used in the optimization in which the weights are modified. To achieve a satisfactory learning rate, 1000 iterations have been performed in training the algorithm. The ANN architecture used is a 1:3:2 as shown in Fig. 3.

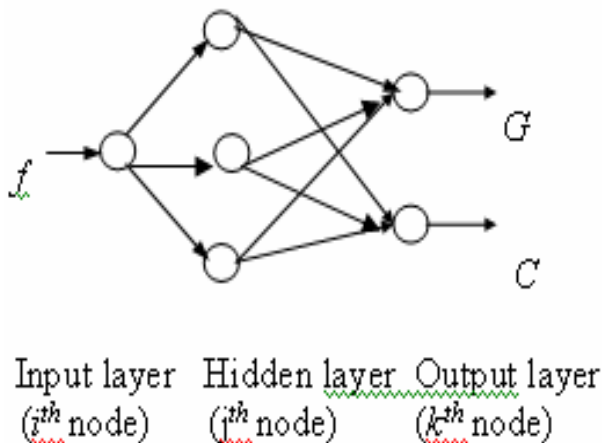


Fig.3. Used Multi Layered Perceptron (MLP) architecture

After the training is completed, the results of the ANN and Modeling methods are compared for 7 test patterns. The input and output values for these patterns are shown in Table 3.

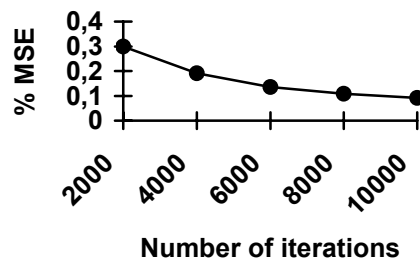
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- [4]. Cerneiro, S. and Marti, J., Evaluation of Corona and Line Models in Electromagnetic Simulations,

Table 3. Comparison of the results of the ANN and Modeling

N	f	Modeling Results		ANN Results	
		$G_m$	$C_m$	$G_{nn}$	$C_{nn}$
1	50	0.758	1920	0.585	1890.25
2	200	1.497	1072	1.599	1083.51
3	1000	4.854	545.59	4.827	511.72
4	1500	6.241	460.16	6.198	472.96
5	2000	7.460	407.79	7.513	429.80
6	2500	8.567	371.31	8.673	378.94
7	3000	9.590	343.94	9.393	327.52

#### 4. DISCUSSIONS

The calculation of conductivity and capacity of transmission line according to the frequencies are studied. The exact values of the conductivity and capacity are calculated by modeling, which has been developed Institute of Saint Petersburg Polytechnic. The method of ANN is used alternatively to compute the conductivity and capacity of transmission line quickly and with small errors. Key values obtained by using the conventional analysis are used in training an ANN algorithm. After training, the algorithm yielded results with considerably low errors as it can be seen in Figure 4. Then, the effects of physical parameters on the conductivity and capacity of transmission line according to the frequencies are investigated using ANN.



The total MSE according to iterations

Fig. 4.

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