

# POWER TRANSMISSION LINE MODELING USING ARTIFICIAL NEURAL NETWORKS IN THE PRESENCE OF NON-FUNDAMENTAL FREQUENCIES

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**Abstract:** This paper presents a new method for neural modeling of power transmission lines particularly for non-fundamental frequencies. The developed Artificial Neural Network (ANN) is based on the comparison of finitely segmented models to uniformly distributed model to identify the appropriate segmented model representing the power line at required frequencies for different levels of accuracy. The line model performance is characterized through waveform including attenuation and phase shift. The simulated results with ANN-based environment parameter variations are compared with numerical methods and validated experimental. The study demonstrates the efficiency and robustness of our proposed method.

**Key Words:** Artificial Neural Network, Harmonic components, Non-Fundamental Frequencies, Power Transmission Line, Segmented Model.

## 1. Introduction

Modern power systems exhibit both fundamental and non-fundamental frequency components [1]. Since the wide spread of power system switches the level of non-fundamental components founded in the network has highly increased e.g. the 15<sup>th</sup> and the 39<sup>th</sup> Harmonic components due to power devices that are incorporated in the network [2]. The presence of these harmonic components would require revisiting commonly adopted models. An investigation of this impact would lead to the development of new models. Currently the non-fundamental frequencies are both passively and actively filtered out [3], it would be highly interesting to recover the unused energy contained in these harmonics. Equally this energy could be stored in specific locations and /or in the line itself and will be converted into real time.

Different studies dealing with the effects of these harmonics and inter-harmonics on the network to gain energy from its storage have been carried out

[4-14]. In fact, harmonic components have direct impact on the behavior of power transmission lines and it is useful to test the validity of the new developed models so that they should be precise, robust and less costly in terms of computing time.

The most commonly used model to study for fundamental frequency is the single lumped parameters configuration e.g. gamma or pi forms for power lines, though this model does not accurately reflects the actual behavior of the line at high frequencies [4], [5]. The related works to power line models depending on frequency are focused on the transient analysis [6], [7] where the models are not used in the steady state studies. Some authors have suggested models with frequency-dependent parameters, but not frequency-dependent structures [6], [8].

The exact number of gamma or pi forms segments that are used to model the power lines is rarely addressed and it is either determined arbitrarily or by trial. The most used models consist of 10 or 20 segments to represent line that is respectively 100 or 200 miles, but this segmentation is neither based on any criterion nor an experimental test. Indeed, none of the works published has demonstrated the accuracy of such a modeling technique. In [10] it has been concluded that the model is completely inaccurate above the cut-off frequency, which is the natural frequency of a segment. Even at frequencies below the cut-off frequency, the frequency performance of the line may be inaccurate.

The stunts circuits (gamma or pi) have already been used in several works, [11] and [12], for modeling lines with parameters-frequency dependency. Some research has been conducted on the relation between the chain segmentation models to the model accuracy [12]. In general, previous works on the subject have treated the problem around switching studies. In [13], Wilson and Schmidt analyzed the

behavior of segmented power line models over a large frequency spectrum and for two loading conditions that are open and short circuits.

Several purely numerical methods have been developed to simulate the finitely segmented model like [14] who proposed a tool for electric power line modeling to determine the adequate structure of the power line model. The approach consists of a step by step computation to achieve the corresponding finitely segmented. However, this tool has larger computational time because it uses an iterative process.

The main purpose of this paper is to develop a new ANN-based technique that allows the user to determine the appropriate segmentation of the line model for studies under non-fundamental frequencies. This technique will give the appropriate line modeling without any iterative computation and in a very short time.

## 2. Proposed Modeling Approach

The proposed approach tends to determine the frequency characteristics of the distributed line model to compare them through a set of parameters for a required loading condition. One takes into account some assumptions such as temperature and current density constant since the line parameters are distributed along the line. The model parameters uniformly distributed mathematically represent the power line model taken as the reference.

To assess the accuracy of the line model, the study is based on the features and performance of wave propagation in particular the attenuation and phase shift of the voltage, then the model is compared to the reference one. Hence sensitive parameters are selected to compare appropriate models representing the line at the desired frequency. The required characteristics are as follows:

1. Validity of the model after the terminal behavior i.e. at the sending and receiving ends;
2. Insensitivity to load changes (these qualities are important for nodal analysis in power system studies).

The selection of parameters and insensitivity to load variations of the finitely segmented model is well justified by [16]. The model performance is characterized by reproduction of wave propagation including wave attenuation and phase shift. For this purpose, quantification of the accuracy of the model

is based on the analysis of loading voltage in term of difference in the magnitude and phase shift between distributed and finitely segmented models:

$$a) \Delta V = \left| |V_{Load}^{Distributed}| - |V_{Load}^{Segmented}| \right|$$

-Difference in loading voltage magnitude

$$b) \Delta \theta = \left| \theta_{Load}^{Distributed} - \theta_{Load}^{Segmented} \right|$$

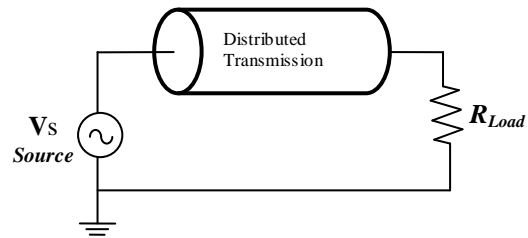
- Difference in loading voltage phase

The desired level of accuracy of the model is expressed in terms of threshold values for the attenuation of the loading voltage and the phase shift. These thresholds are expressed by:

$\Delta V_{Threshold}$  : Threshold value on difference in loading voltage magnitude

$\Delta \theta_{Threshold}$  : Threshold value on difference in loading voltage phase

These threshold values representing the desired accuracy depend on the application of the resulting model. The user will select according to this application, whether the most important role is due to the attenuation of voltage or to the phase shift. The frequency characteristics of the line model with distributed parameters (Fig.1) can be determined analytically or through simulation software. The behavior of the  $\pi$  or gamma model finitely segmented is simulated with the same frequency, and then compared to the reference model through a set of defined parameters.



**Fig.1.** Distributed Line Model Used in Simulation

As mathematically expressed by the above equations with the distributed line model, the steady-state voltages and currents can be determined at any point along the line.

However, the relationship between the terminal voltages and the terminal currents, i.e. at the sending and receiving ends, are often sufficient in power system studies since nodal analysis is conducted:

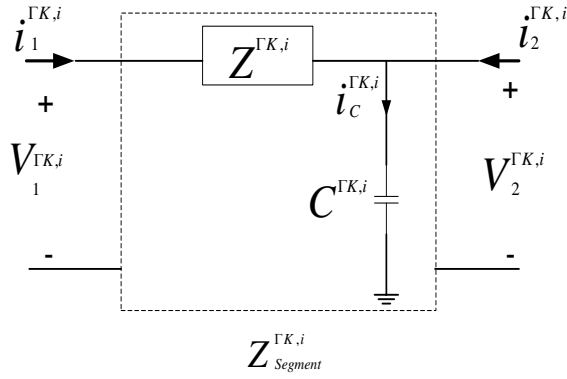
$$V_s = V_R \cosh(\gamma \ell) + Z_c I_R \sinh(\gamma \ell) \quad (1)$$

$$I_s = I_R \cosh(\gamma \ell) + \frac{V_R}{Z_c} \sinh(\gamma \ell) \quad (2)$$

With  $\gamma$ : is the propagation constant  $\ell$ : is the line length and  $Z_c$ : is the characteristic impedance

#### Model Development (finitely segmented):

A generic one-segment  $\Gamma$  (gamma) model is shown in Figure 2. Although other lumped parameter models, such as the  $\pi$  (pi) form, could have been selected

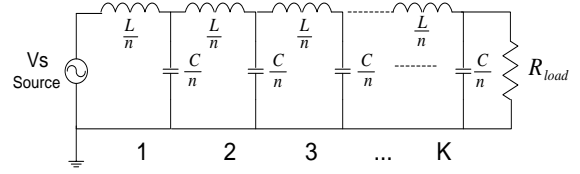


**Fig.2.** Diagram of the  $i$ -th-segment of a  $\Gamma$  line model.

- $K$ : total number of segments
- $i$ : segment number from receiving end
- $v_s^{\Gamma K, i}$ : voltage waveform at the sending-end of the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type
- $i_s^{\Gamma K, i}$ : current waveform through the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type, seen at the sending-end
- $v_R^{\Gamma K, i}$ : voltage waveform at the receiving-end of the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model
- $i_R^{\Gamma K, i}$ : current waveform through the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type, seen at the receiving-end
- $i_c^{\Gamma K, i}$ : current waveform through the shunt capacitor in the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type.
- $Z^{\Gamma K, i}$ : 'series' ( $S$ ) impedance of the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type
- $C^{\Gamma K, i}$ : capacitance at the receiving-end side of the  $i$ -th segment of stage  $K$  in the  $\Gamma$ -model type

The  $K$ -segments models (Fig 3) were obtained by dividing evenly the basic  $\Gamma$ -model in a number  $K$  ( $K = 1, 2, 3 \dots n$ ). When  $n = \infty$ , we obtain the distributed parameter model.

Figure 3 shows the basic model of a lossless finitely segmented line with  $K$  segments.



**Fig.3.**  $K$ -Segments  $\Gamma$  Line Model of a Lossless Line

### 3. Modeling with Neural Networks

The artificial neural networks (ANN) are taking part of modern techniques for modeling. They offer an alternative to mathematical modeling where system models are nonparametric statistics and non-linear. Their main advantage lies in their capacity of generalization. ANN have attracted much attention due to their computational speed and robustness. Learning and architecture design of the ANN are based on a comparative approach of the line governed by the distributed model as a reference and the finitely segmented models under various predefined frequencies and accuracy.

#### A. Database Set

The selection of the finitely segmented model in gamma configuration and the test application are stated in [14]. Further models to localized parameter such as the  $\pi$ -form configuration could be selected. The Cable characteristics at the fundamental frequency of 60 Hz are illustrated in Table1:

**Table 1:** Characteristics of the line

$R_\ell$	$0.0612 \Omega/mi$	line resistance per unit length
$X_\ell$	$0.6081 \Omega/mi$	line reactance per unit length
$X_c$	$0.1423 M\Omega/mi$	reactance of the shunt element per unit length

The inductance  $L$  and shunt capacitance  $C$  for  $\Gamma$ -Model are then being calculated with the following expressions:

$$L = \frac{X_\ell}{\omega} \cdot \ell = \frac{X_\ell}{2\pi f} \cdot \ell \quad (3)$$

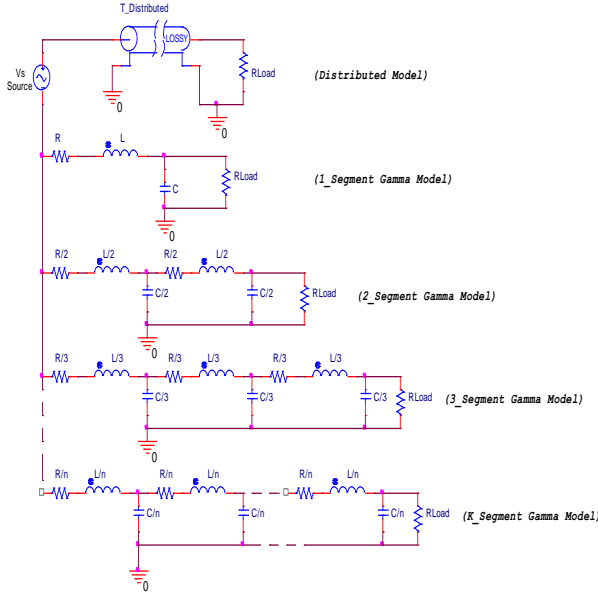
$$C = \frac{1}{\omega X_c} \cdot \ell = \frac{1}{2\pi f X_c} \cdot \ell \quad (4)$$

Where

$\ell$ : is length of the line in kilometers (receiving end to sending end);  $R_{Load}$ : is a constant load kept the same for every model.

The models are simulated in a desired frequency range.  $|V_{load}|$  and  $\theta_{load}$  are recorded to quantify the wave attenuation and phase shift with the desired accuracy.

The whole model is simulated using cadence PSpice software as shown in Figure 4, using the assembly of the distributed model as a reference and the finitely segmented models.



**Fig.4.** Cadence Pspice Schematic for Distributed and 1 through K-Segment gamma Models

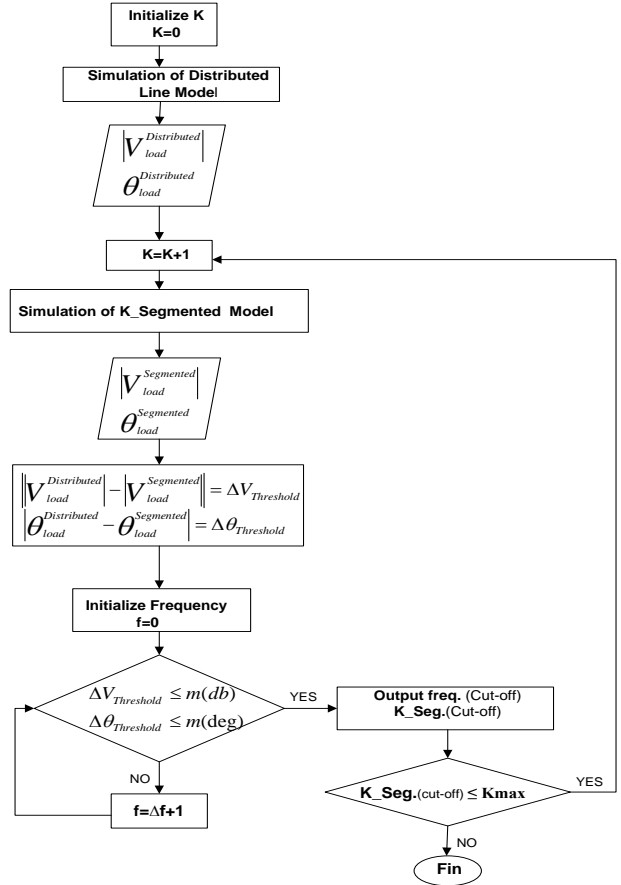
In order to study the harmonics in the power lines, the frequency is scanned in the considered range under the same supply voltage and with the same loading. The simulation was carried out for Falcon cable lengths with different models segmented in gamma configuration.

The differences:  $\left| |V_{Load}^{Distributed}| - |V_{Load}^{Segmented}| \right|$  and

$|\theta_{Load}^{Distributed} - \theta_{Load}^{Segmented}|$  were computed and

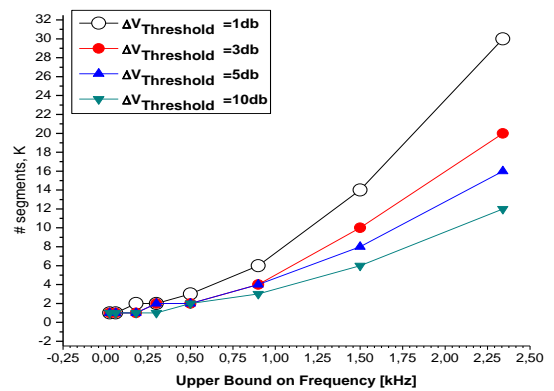
the segmented model of the appropriate precision level has been identified.

The flowchart of the proposed approach is depicted in Fig.5.



**Fig.5.** The flow chart of the proposed modeling

From the simulation results, the appropriate number of segments line model is obtained for different lengths and levels of accuracy in Fig.6.



**Fig.6.** Frequency change vs. Segment number K (#accuracy levels)

Therefore, a single lumped equivalent circuit while sufficient for line studies at the fundamental frequency can cover the line at higher frequencies. On the other hand, the differences ( $\Delta V$ ) of voltage attenuation and the phase ( $\Delta\theta$ ) between the

distributed and the finitely segmented models vary with the number of segments. For longer-length line, the same model segmentation as a shorter line maintains a certain level of accuracy for a smaller frequency range than the shorter line i.e. the “cut-off” happens at lower frequencies in a longer line than in a shorter one.

## B. Implementation of ANN

The proposed neural network is a multilayer perceptron (MLP) type with a supervised learning from a given data base formed by simulation with Cadence PSpice software for different cable lengths and different levels of precision. For the ANN outputs illustrated in figure 7, the finitely segmented model is defined as the number of segments and the appropriate parameters for a given line, whereas the inputs of the ANN include Cable type i.e. parameters per length unit, the frequencies of interest with the desired accuracy of the model expressed in terms of threshold values selected for the voltage attenuation:  $\Delta V_{\text{Threshold}}$  and phase  $\Delta \theta_{\text{Threshold}}$ . Another input parameter is reserved to the user in order to select among the voltage attenuation or the phase shift according to his requirement. The first layer of the neural network contains seven neurons and one neuron (the eighth) is selected depending on the model objective either  $\Delta V_{\text{Threshold}}$  or  $\Delta \theta_{\text{Threshold}}$ .

### Network structure optimisation

During the first stage of network optimisation the fundamental parameters of the network have been tested to investigate which one gives the best performance. These are the transfer functions for each layer and the training algorithms.

The transfer functions used were the tansig function, for the hidden layer and the purelin function, for the output layer. Both are very common choices for this type of ANN (Vogl, Mangis, Rigler, Zink, & Alkon, 1988; Hagan, Demuth, & Beale, 1996; Math Works, 2004).

Six trainings algorithms were tested for the same network there is no specific rule for the selection of the number of neurons in the hidden layer or the number of hidden layers that will produce the optimum results for a given problem. The number of neurons in the hidden layer is usually determined by trial and error. The Levenberg–Marguardt (TRAINLM and TRAINSCG) were found to give the best performance.

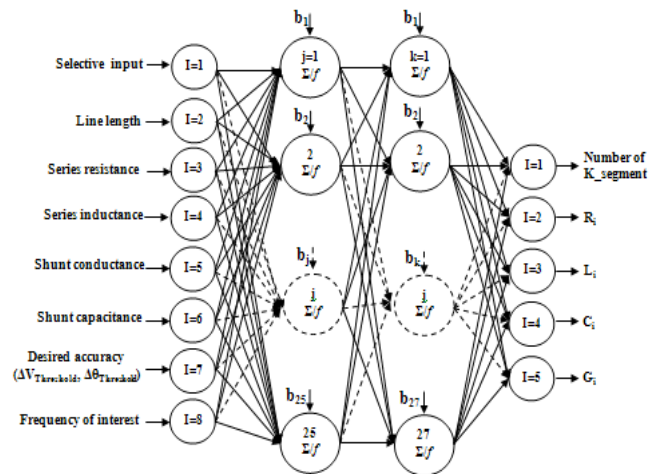
The two selected algorithms have been chosen for training with the normalized data. The TRAINLM with the Levenberg–Marguardt algorithm was found to work much better. The MMM pre-processing method (Min–Max Method) has resulted in a much better performance, in terms of consistency and error performance.

The optimisation stage of ANN has focused on testing different neural network architectures by altering the number of neurons in the hidden layer and the number of the hidden layers. The results of the network performance to different tested architectures are shown in table 2.

**Table 2:** Different tested architectures

Network topology	Final ARRE(%)	Epochs	Time (min)
[8 25 27 5]*	1.02	500	29
[8 20 10 5]	2.4	1000	126
[8 15 15 5]	7.15	400	20
[8 25 25 5]	2.77	500	40
[8 30 25 5]	1.75	129	50
[8 20 5]	2.1	10	4
[8 25 5]	2.7	20	5
[8 30 5]	3.85	200	10

The application of network strategy for modeling the line for inter-harmonic frequencies is given by the ANN model with an optimized architecture (Figure 7) whose structure is shown in Table 3.



**Fig.7.** Architecture of the optimized neural network

The ANN obtained was trained by a database matrix of dimension (711, 12) with normalized values. Once the learning phase achieved the ANN is tested with a new set of input/output that forms the basis of

generalization. This step verifies the behavior of ANN on cases not learned. The optimization results

after 1000 iterations with an error performance of  $1.02 \times 10^{-5}$  are presented in Table 4.

**Table 3.** Structure of optimized ANN

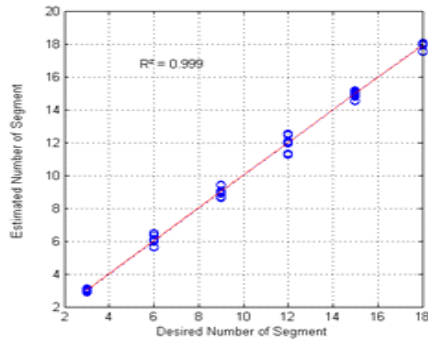
Type network	Input Layer	1 <sup>st</sup> hidden Layer		2 <sup>nd</sup> hidden Layer		Output Layer		Training Algorithm
	Nb. of neurons	Nb. of neurons	Activation Function	Nb. of neurons	Activation Function	Nb. of neurons	Activation Function	
MLP	8	25	TANSIG	27	TANSIG	5	PURLING	TRINLM

**Table 4.** Error of the ANN model.

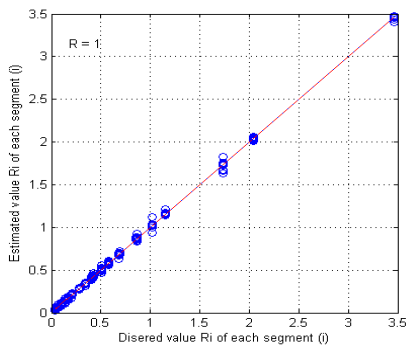
ANN	Output 1	Output 2	Output 3	Output 4	Output 5
MAE (%) Test case	AARE=1.2110	1.1692	0.0311	0.3587	0
MAE (%) Case generalization	AARE=1.0270	1.0642	0.0282	0.3248	0

#### 4. Results and discussion

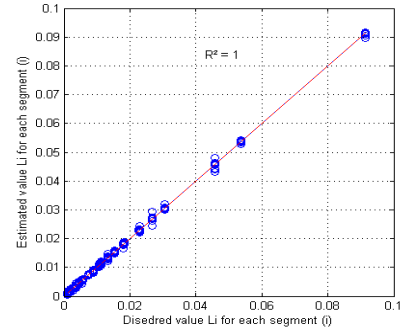
Figures 8a, 8b, 8c and 8d illustrate the desired outputs and those predicted by ANN which lead to a very satisfactory correlation. This demonstrate the effectiveness of the developed neural model and that is characterized by an optimal capacity of prediction for segment number and the parameters forming the finitely segmented model which cover the inter-harmonic frequencies of the power transmission line.



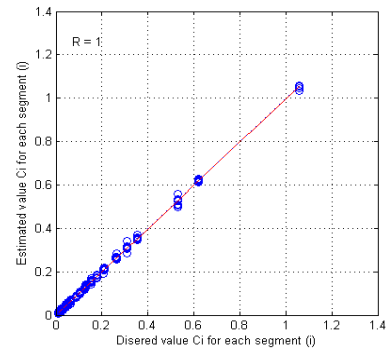
a) Output 1



b) Output 2



c) Output 3

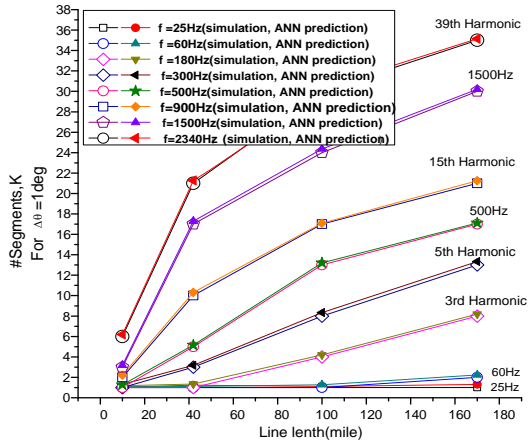


d) Output 4

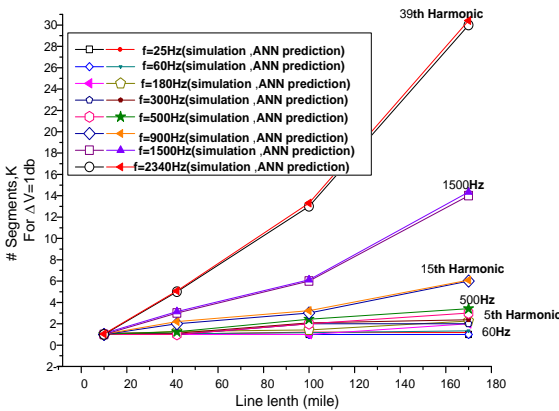
**Fig.8.** Comparison between desired outputs and those calculated by ANN. (a) Segments Number, (b) Segment Resistance, (c) Segment inductance, (d) Segment capacity.

Test results are carried out from a new base including data not used in the learning phase. The validation test given by figures 9 and 10 representing the segment number changes ( $\Delta\theta=1\text{deg}$  and  $\Delta V=1\text{db}$ ) against the line length for

intrinsic frequencies show good agreement between simulated and predicted values which confirms the performance of our proposed ANN.



**Fig.9.** Segment Number Variation ( $\Delta\theta$  Threshold) vs. the line length for different frequencies.



**Fig.10.** Segment Number Variation ( $\Delta V$  Threshold) vs. the line length for different frequencies for optimized ANN.

The differences in phase shift of Fig.9 and voltage attenuation of Fig.10 between the distributed and the finitely segmented line models vary with the number of segments. Furthermore a single lumped equivalent circuit, while sufficient for studies the line at the fundamental frequency, cannot cover the line of non-fundamental frequencies. In order to achieve the same accuracy level, at any given frequency, a higher segmentation was needed for the longer line than for the shorter line.

The behavior of finitely segmented model compared to the distributed model with respect to the length of the line is the same qualitatively. On the other hand, it is quantitatively different i.e. the same model can represent the line for different lengths with the same accuracy than assumed for a similar frequency range inversely proportional to the length of the line.

## 5.Conclusion

This paper presents a new neural network modeling for power line to predict the appropriate finitely segmented model to steady-state analysis of non-fundamental frequencies with a predefined accuracy level.

The optimized architecture ANN- MLP enables to predict the number of segments with a high performance error. The simulation was tested on a real line confirming the robustness and the predictive ability of our model that is only based on the characteristics data of the line.

For future works it would be worth it to develop the neural network model by including the parameters per length unit as a function of frequency and temperature along the line. This will certainly have an impact on the obtained finitely segmented model.

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