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Prediction of Voltages on Mitigated Pipelines Paralleling Electric Transmission Lines Using an Artificial Neural Network

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Abstract

This paper presents a technique based on the development of an artificial neural network (ANN) model for predicting the total voltage on mitigated pipelines due to the effect of the inductive and conductive ac interference under fault conditions. The pipeline shared right-of-way with high voltage power lines and it is mitigated by gradient control wires. In particular, the developed ANN predicts the mitigated pipeline voltage under different soil resistivities, fault currents and separation distances. The results indicate reasonable agreement between model prediction and calculated values. The results also demonstrate that the ANN-based model developed in this work can predict the voltage after applying mitigation system with high accuracy. The accuracy of the predicted voltage is very important to protect the overall pipeline integrity and make the pipeline and appurtenances safe for operating personnel.

Keywords

Conductive interference, Inductive interference, Pipeline Voltages, Corrosion, *Mitigation*, Artificial Neural Network.

1. INTRODUCTION

Study of interference effects from AC power lines on nearby conductors such as pipelines, railways and communication lines resulted in many papers, standard and reports [1-13]. In this paper a technique based on the development of an artificial neural network (ANN) model is used to predict the total voltage on mitigated pipelines under fault conditions.

Gas/Oil/water pipelines and power lines often use the same way to minimize land use, to reduce both the installation cost and damage to the environment. Induced ac voltage on unmitigated pipeline can reach thousands of volts during fault conditions. This induced voltage is hazardous to personnel who may come in contact with the exposed structures connected with the pipelines. It can also result in damage to the pipeline and its coating. Excessive coating stress voltages (the difference between the pipeline steel potential and local soil potential) can result in puncture or degradation of coating leading to accelerated corrosion [4]. These voltages can also result in damaging the insulating flanges and cathodic protection equipment. Moreover, to elevate these problems a mitigation system should be designed.

Considerable efforts have been placed on the applications of ANNs to power systems. Several interesting applications of ANNs to power system problems have been published [14-17], and it has been shown that ANNs have great potential in power system on-line and off-line applications. In this paper, an approach using an ANN is proposed to predict the voltage on mitigated pipelines built in power lines right-of-way after using the mitigation system. The multilayer feed forward ANN with the error back propagation training method is employed. The input to the ANN is the system parameters (fault current, soil resistivity, and separation distance between power lines and pipelines) and the output is the mitigated pipeline voltage. The results reported in this paper present the predicted pipeline voltage subjected to inductive and conductive coupling from an overhead power transmission lines after applying the mitigation system.

2. COMPUTER SYSTEM MODEL

This study is based on a typical field case study which consists of a 10 km parallelism between a well coated 16 " pipeline and 132 kV transmission lines. Fig. 1 shows the computer circuit model used to calculate the induced voltage on the mitigated pipeline. The data required for training the ANN model

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for the present study has been obtained using the ROW and MALZ programs [12]. The training data are given in Table 1.

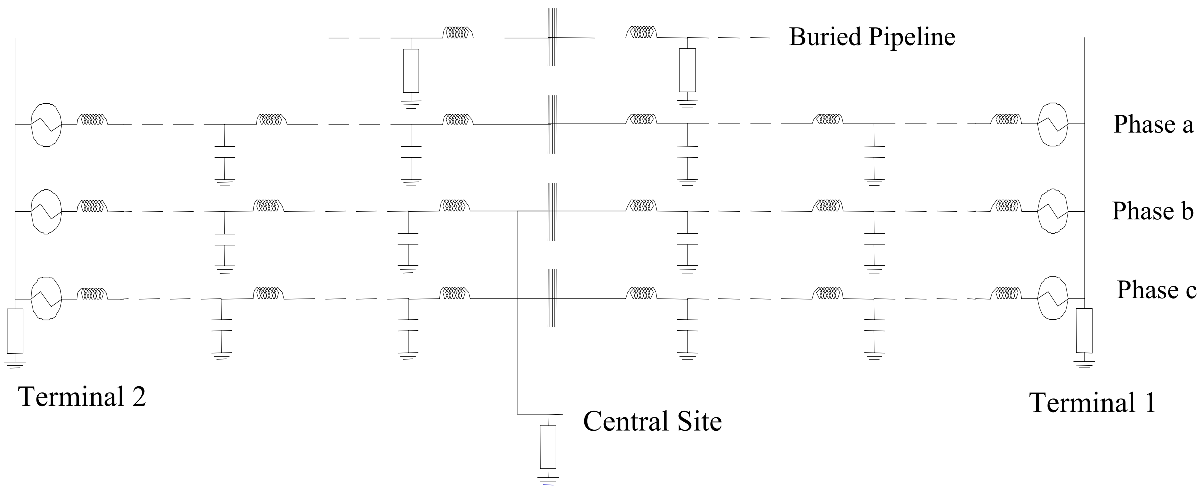

Fig. 1 Simulated circuit model

It is worth nothing that the results obtained, for the inductive component, using *ROW* program have been verified by the following formula [9] and good agreement has been obtained [18].

$$E_f = I_f \left(\frac{5}{8}\right) \frac{f}{60} [0.0954 + j\,0.2794 \log \frac{D_{ex}}{D_{ax}}] \tag{1}$$

where:

E_f : *The induced voltage on mitigated pipeline during the fault, V/km*
I_f : *The fault current, A*
D_{ex} : *The depth of earth return path, m*

D_{ax} : *The separation between phase conductor and the pipeline, m*

f : *frequency, Hz*
$j : \sqrt{-1}$

The depth of earth return path is given as

$$D_{ex} = 600 \sqrt{\frac{\rho}{f}} \tag{2}$$

The maximum induced potential is given by the approximated formula

$$V_{Max} = \frac{E_f}{\gamma} \quad (3)$$

where:

γ is the propagation constant of pipe in 1/km.

ρ : *The soil resistivity* , $\Omega.m$

$\gamma = \sqrt{ZY}$, where Z is the pipe self impedance and Y is the pipe shunt admittance per unit length.

Table 1: Peak voltage on mitigated pipeline at different values of phase to ground fault currents I_f and soil resistivity ρ

Peak Voltage (V)				
Separation (m)	I_f =5kA & ρ=100 Ω.m	I_f =2kA & ρ=100 Ω.m	I_f =3kA & ρ=200 Ω.m	I_f =4kA & ρ=300 Ω.m
100	942	361	708	1095
200	646	247	500	767
400	403	153	310	495
600	275	107	210	359
800	195	79	150	282
1000	155.8	60	137	224

2. Mitigation System

In the past, different types of mitigation strategies have been employed, but many have been found to be either very expensive, as lumped grounding, or ineffective or even hazardous like cancellation wires [13]. The preferred way is the gradient control wires. These wires not only provide good grounding for the pipe and thus lower the absolute value of the pipeline potentials, they also raise earth potentials in the vicinity of the pipeline as a result the difference in potential between the pipeline and the local earth is reduced, thus providing reduced touch voltages and decreasing coating stress voltages. The gradient control wires are zinc ribbon anode and it may be placed parallel to the pipeline and connected at different intervals as shown in Fig. 2. Typical connection intervals vary from 152-609m.

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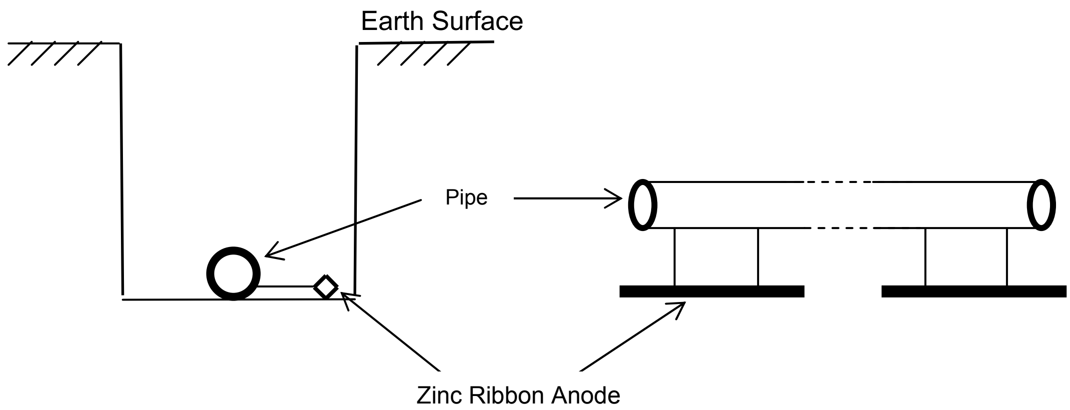

Fig. 2 Connection of the mitigation wire to the pipelines

3. ARTIFICIAL NEURAL NETWORK

Artificial Neural networks (ANN) are one of a group of intelligence technologies for data analysis that differ from other classical analysis techniques by *learning* about your chosen subject from the data you provide them, rather than being programmed by the user in a traditional sense. Neural networks gather their knowledge by detecting the patterns and relationships in your data, learning from relationships and adapting to change. ANNs can handle multivariable problems. They have the potential to describe highly non-linear relationships. Therefore, the application of artificial neural networks to modeling complex relationships has recently become available to capture those non-linear features that a conventional statistical technique (e.g., regression models) might overlook [19]. Heravi et al. [20] indicated that ANN provides a general framework, which can approximate any type of non-linearity in the data. In general, ANN applications in engineering have received wide acceptance [14,15,16,17]. The popularity and acceptance of this technique stems from ANNs features that are particularly attractive for data analysis. These features include handling of fragmented and noisy data; speed inherent to parallel distributed architectures, generalization capability over new data, ability to effectively incorporate a large number of input parameters, in addition to its capability of modeling nonlinear systems. Despite these great features and successful performance of ANN models, there are many inconsistent reports in the literature regarding ANN performance in forecasting time series data. Zhang et al. [21] and Zhang, G. [22] indicated that the inconsistencies in ANN performance may be due to the large number of factors including network structure, training methods, and sample data. These factors may affect the forecasting ability of the networks. Other factors cited in the literature are that ANN model is being a black-box method. There is no explicit form to explain and analyze the relationship between input and output variables. This causes difficulties in interpreting results from the network. In addition, there are over fitting problems associated with ANN models. These issues and others, however, became important research areas and solutions in tackling these problems are being made [23-24].

The major building block for any ANN architecture is the processing element or neuron. These neurons are located in one of three types of layers: the input layer, the hidden layer, or the output layer as shown in figure 3. The input neurons receive data from the outside environment, the hidden neurons receive signals from all of the neurons in the preceding layer, and the output neurons send information back to the external environment. These neurons are connected together by a line of communication called connection. Stanley [25] indicated that the way in which the neurons are connected to each other in a network typology has a great effect on the operation and performance of the network. ANN models come in a variety of typologies or paradigms. Simpson [26] provides a coherent description of 27 different popular ANN paradigms and presents comparative analyses, applications, and implementations of these paradigms. A detailed discussion of the different neural network paradigms and their training and recall operations is out of the scope of this paper. Here only some of the relevant issues related to back-propagation network are presented. For the sake of brevity we refrain from discussing the details of neural network principles for details the reader is referred to [25-29] and for the neural network methodology refer to [30-32] for more comprehensive treatment.

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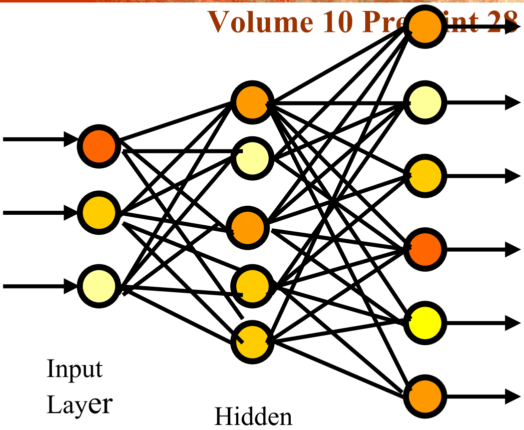

Fig. 3 Typical back-propagation architecture

3.2 ANN MODEL DEVELOPMENT

Prior to conducting the network training operation using the back propagation paradigm [25-26], training sets of 60 cases were obtained from the calculated data for 132 kV line with different values of fault currents, soil resistivities and separation distances. This data set covers different situations that could possibly take place. Typical training patterns used as part of the training data set are presented in Tables 1. As shown in Fig. 4, the ANN model used in this work consists of 4 input nodes representing Fault current, Soil resistivity, separation distance, and mitigation. The output consisted of one node representing the mitigated pipeline voltage. The training process was performed using the NeuroShell® simulator [33].

After several adjustments to the network parameters, the network converged to a threshold of 0.00001 using 3 hidden nodes. The trained model prediction was in good agreement with the actual results as demonstrated by Fig. 5, hence, producing R^2 value of 0.9978. This indicates that approximately 99.78% of the variation in the mitigated pipeline voltage could be explained by the four selected input variables and the data used for model development. Having trained the network successfully, the next step is to test the network in order to judge its performance and to determine whether the predicted results confirm with the actual results.

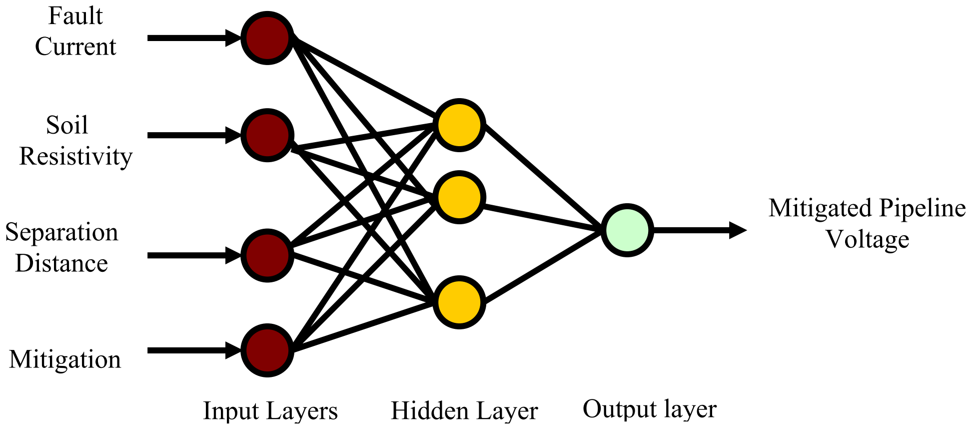

Fig. 4 The Architecture of the developed ANN model.

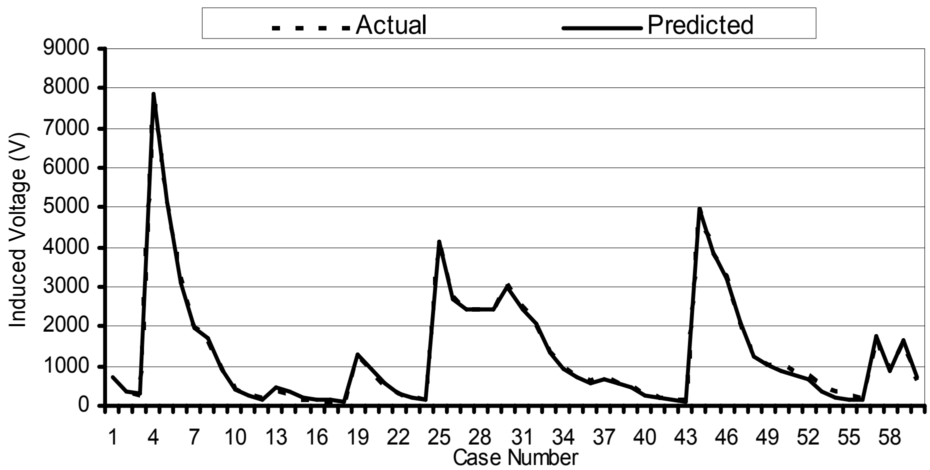

Fig. 5 Actual and predicted gas pipeline induced voltages for the training set.

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4. RESULTS AND DISCUSSIONS

The trained model is assumed to be successful if the model gives good results for the test set. Using the 11 cases allocated for the testing set, the model-input parameters were entered consecutively for each case and a prediction for the pipeline voltage was obtained. The results were then compared with the actual results of the 11 cases in question as shown in Fig. 6. The statistical analysis of these results indicates that the R^2 value for the testing set was 0.9933. This high generalization capability indicates that the ANN model predicted with 99.3% accuracy. The results of actual and predicted mitigated pipeline voltage at different fault currents and soil resistivities are shown in Fig. 7. These results also demonstrate that the ANN-based model developed in this work can be used for future analysis.

The partitioning method of the connection weights of the network [34-35] was used to study the relative percent contribution of each of the input variables. The method involves partitioning the hidden-output connection weights of each hidden neuron into components associated with each input neuron. Details can be found in the above two references since detailed discussion of this method is out of the scope of this paper. Here only a simplification of the proposed algorithm is presented [36].

1. For each hidden neuron *h*, divide the absolute value of the input-hidden layer connection weight by the sum of the absolute value of the input-hidden layer connection weight of all input neurons, i.e.

For h=1 to nh,

For i=1 to ni,

$$Q_{ih} = \frac{|W_{ih}|}{\sum_{i=1}^{ni} |W_{ih}|} \tag{4}$$

end,

end.

2. For each input neuron i, divide the sum of the Q_{ih} for each hidden neuron by the sum for each hidden neuron of the sum for each input neuron of Q_{ih} ; multiply by 100. The relative importance of all output weights attributable to the given input variable is then obtained.

$$RI(\%) = \frac{\sum_{h=1}^{nh} Q_{ih}}{\sum_{h=1}^{nh} \sum_{i=1}^{ni} Q_{ih}} X100 \qquad (5)$$

end.

Using this method for the ANN model, It was found that the contribution of the separation distance (d) in meter on the mitigated pipeline voltage levels was approximately 48% and the mitigation effect was 30% while the remaining 22% was attributed to soil resistivity (11.3%) and the phase current (10.1%). These clearly indicate that separation distance between the power lines and gas pipeline right-of-way should be determined carefully and power lines should be kept at a safe distance from pipelines. It also demonstrates that mitigation is an important factor in controlling the magnitude of the pipeline voltage. Fig. 7 presents a comparison between the actual and predicted mitigated pipeline voltages at different fault currents and different soil resistivities for a range of separation distances. It is clear that there is good agreement between the actual and predicted results. Hence, the ANN-based model developed in this work can predict the mitigated pipeline voltage with high accuracy. The accuracy of the predicted voltage is very important for designing suitable mitigation systems that will increase the overall pipeline integrity and make the pipeline and appurtenances safe for operating personnel.

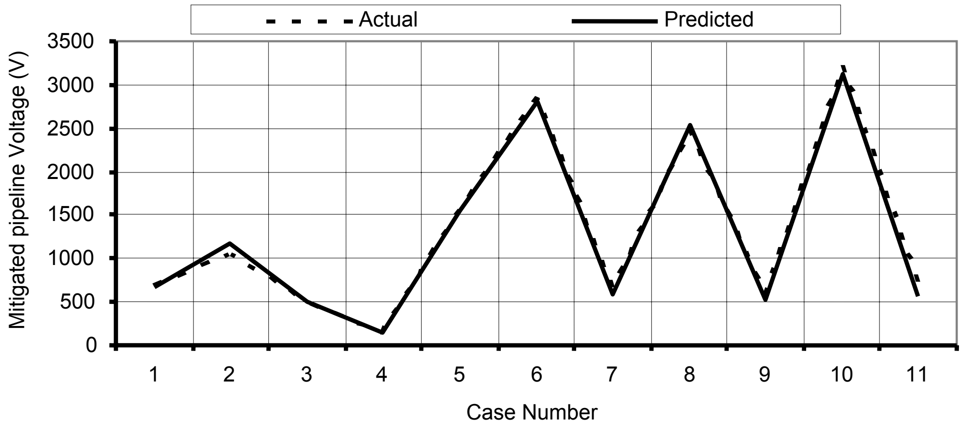

Fig. 6 Actual and predicted mitigated pipeline voltage for testing set

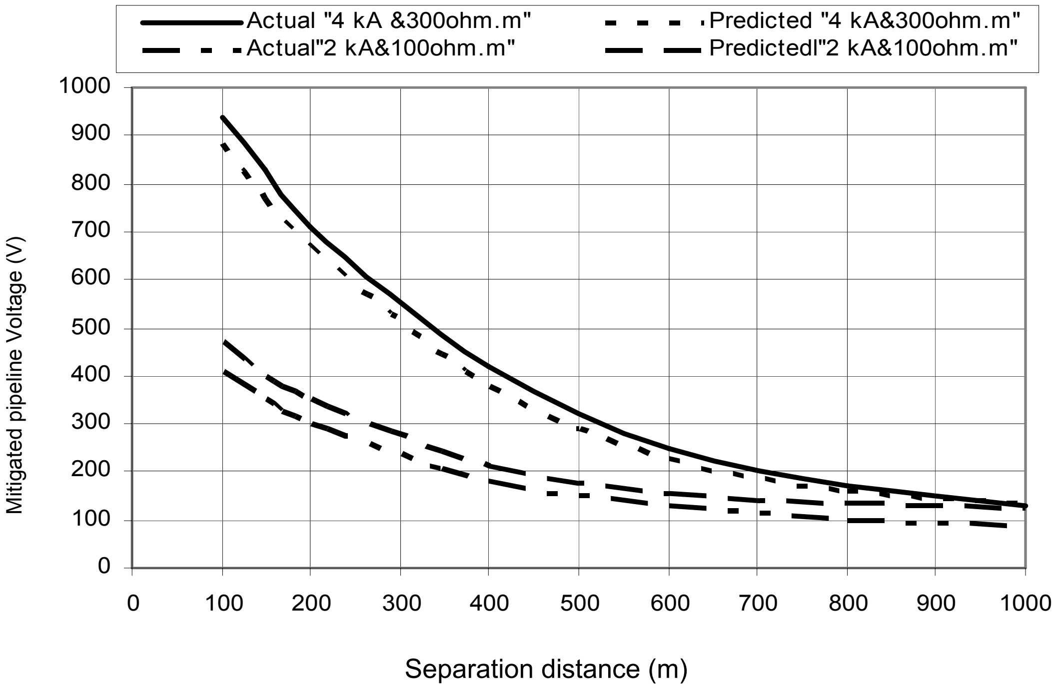

Fig. 7 Mitigated pipeline voltages at different fault currents and soil resistivities

5. CONCLUSION

In this work an artificial neural network (ANN) model has been developed for predicting the voltage on mitigated pipelines built in overhead power lines right-of-way. The actual system parameters, mitigation system, fault current, soil resistivity, and separation distance, as the ANN input and the ANN provides the predicting of mitigated pipeline voltages as its output.

It was found that the neural network model consistently gives superior predictions and the results produced were good. The R-squared values were found to be high. The R-squared for the training set was of 0.9978 while the testing set was 0.9933. The high testing set R-squared value indicates a high generalization capability of the developed model.

The relative importance of the various input variables was also investigated. Clearly, this study indicated the potential of the neural network approach for capturing the linear and non-linear interactions between the pipeline voltage levels and the input variables used and for the identification of the relative importance of these variables

APPENDIX

The following summarizes all system data used in this study. These data characterize the base case.

Pipeline

Coating Resistance: *20000* $\Omega.m^2$ *(*$15665\ \Omega.m$)

Coating thickness: 0.0036m

Outer Diameter: *0.4064 m*

Inner Diameter: *0.39923 m*

Burial depth: *0.5 m*

Relative Resistivity: *17* (with respect to annealed copper).

Relative permeability: *250* (with respect to free space).

Grounding: *None*

Overhead Transmission line

AAAC (single-ELM) 132 kV

G.M.R: *0.7122 cm*

Conductor outer radius: *0.94 cm*

Outer strand radius: *0.188 cm*

Number of strands: *19*

Fault current (phase-to-ground fault): 5 kA

System

Length of parallel corridor: *10 km*

Soil Resistivity ρ: 100 $\Omega .m$

Separation distance: 100 m

Mitigation System

Gradient control wire: Zinc ribbon with diamond-shaped 12.7x14.28 mm (1/2 x9/6 inch).

Mitigation wire resistivity: 3.47

Mitigation wire permeability: 1

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