Neural Network Based Model for Estimating the Resistance of Outdoor Distribution Substation Grounding

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I. INTRODUCTION

Grounding is one of the most important parts of an electrical system. Earthing systems are done to protect the power system and the personnel from the danger of electrical shocks. Ceylon Electricity Board (CEB) uses a special structure for transformer earthing arrangement. The used structure is copper bonded earth rod with a concrete filled steel cage.

Due to the complexity of the structure and the nonlinear variations in soil parameters, it is challenging to determine resistance before implementing the structure.

We can use an analytical formula for structures to find the resistance. [4] But for complex structure, as we use here, it is challenging to produce an analytical formula. The other solution is to use a Finite Element Method(FEM) to solve the problem.[2] But is also a time-consuming task.[1] So, we propose a combination of FEM and a neural network-based solution for this task.[1]. We propose to generate a data set using FEM and implement it in a neural network.

II. LITERATURE REVIEW

Numerical simulation of electromagnetic fields is a technique used in electrical engineering to design, optimize, and validate equipment behavior in the field. The Finite Element Method (FEM) is the most commonly used tool for this purpose. FEM offers accuracy and flexibility in modeling complex geometries and boundary conditions and can handle nonlinear material properties and dynamic behavior. However, FEM requires significant hardware tools and time consumption. Every configuration requires another FEA to be performed.

There are four types of artificial neural networks: Forward Neural Networks, Radial Basis Function (RBF) Neural Networks, Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs). Feedforward Neural Networks are the simplest type and have no feedback loops or cycles. RBF neural networks have a hidden layer with radial basis functions, are suitable for interpolation and function approximation, and use linear regression to determine the weights of the output layer. RNNs have feedback loops or cycles, store, and process sequential or temporal data, can model complex dynamic systems, and capture long-term dependencies in the data. CNNs have convolutional layers and are designed to exploit the spatial structure and locality of the data. The best method to generalize the FEA result for any variation of the geometrical and material parameters of the base configuration is to use a combination of FEA and neural networks. Neural networks are well-known for their capability to approximate functions using a concept called "regression." When training the neural network, it is recommended to use only 60% of the available data, with 20% for testing and 20% for cross-validation.

In terms of frequency domain vs. DC analysis, the earth resistance for low-frequency AC and DC is almost the same. However, the resistance starts to show a significant deviation in the MHz range. As the frequency of AC rises, the earth's impedance will increase. Impedance with a phase angle less than ±5° is considered resistive.

III. METHODOLOGY

In this project, we propose a method to approximate the resistance of transformer neutral earthing of outdoor distribution substations. This model contains two subsections, simulating the model using COMSOL, and designing a neural network-based solution and an empirical solution.

A. *Simulating the model using COMSOL*

COMSOL is a simulation software used to determine various parameters and coefficients in our calculations. In the simulation software, we will design a model in which we can vary several parameters. By varying these parameters, we expect different observations.

B. *Designing a neural network-based solution*

We are expecting to retrieve data from the above-mentioned simulation. After gathering enough data sets, we will train the neural network model by adding the data. The neural network will be evaluated multiple times to increase accuracy.

IV. Model Design

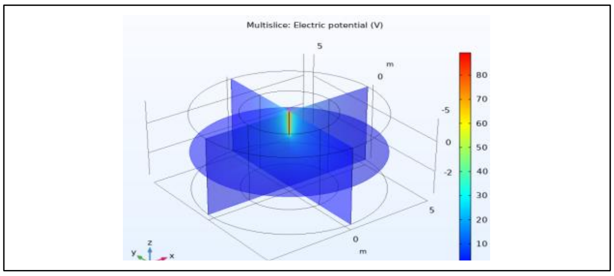

Figure 1

Figure 1 illustrates the view of the single Copper Rod COMSOL model that we developed.

V. Results and Discussion

A. *Frequency domain and Direct Current analysis*

We simulated a single Copper Rod in COMSOL, injecting an Alternating Current of 50Hz and a Direct Current. From the results we obtained it was confirmed that the Impedance of the Alternating Current source of 50Hz was almost equal to the Resistance of the Direct Current source. There was a slight difference in the values in the nano-ohm(nΩ) range. It was concluded that simulating the COMSOL model with a Direct Current source would not change the results.

B. *Analysis of the single Copper Rod*

When simulating the single Copper Rod, we had to consider several facts. The considered soil radius should be higher than the length of the Copper Rod. The considered soil depth should be at least 2 times the length of the Copper Rod. The model that has these parameters will cover more than 90% of the total soil resistance.

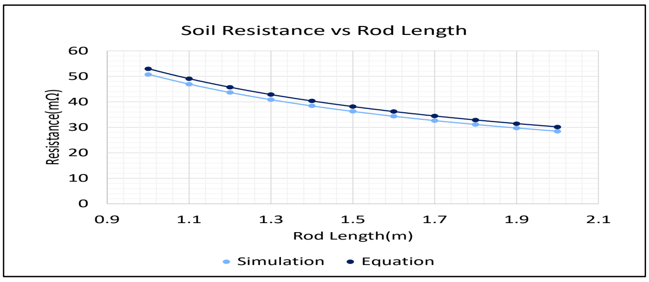

Figure 2

We used the soil layer with a radius of 7m and a depth of 7m. Therefore, we were able to contain more than 90% of soil resistivity in our model.

Initially, we needed to validate that the simulation software would give accurate results. For this, we changed the parameters of the Copper Rod and simulated to get a data set of the resistance. We also calculated the resistance from the empirical equation for the same parameters.

The results obtained by changing the Copper Rod length are presented in Figure 2. The similarity between simulation results and the results taken from the empirical formula can be observed in Figure 2.

C. *Analysis of the soil layer*

As said earlier, the soil layer which we considered consists of 90% of the total soil resistance. This value can be increased by considering more of the soil layer. However, we cannot simulate a very large soil layer since it will require a large number of virtual resources.

Figure 3 presents the data gathered by changing the radius and length of the soil layer. The empirical equation result can also be observed. As the value of the soil radius gets higher, the change in the soil resistance per increased radius becomes lower. Therefore, we can find a value for the soil radius which the change in soil resistance will be negligible for higher radius values. This value will not reach the empirical equation value since the empirical equation is not 100% accurate for all situations.

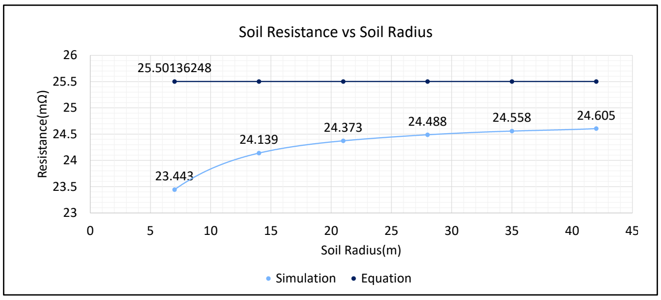

Figure 3

VI. Conclusion

We have been able to prove the accuracy of using COMSOL for this project. Figure 4 illustrates the side view and Figure 5 illustrates the top view of our final design. The actual structure will be made with a Copper rod in the center and a steel cage. The steel cage will have a depth of 1.2m and a radius of 0.5m. The radius of the metal rods is 6mm. Cement is used for fixing the structure. This is the progress of our project, and we will continue to develop the model that we designed for the CEB. This structure will be used to generate the data for the Neural Network. The Neural Network will be trained by a proportion of this data while another proportion will be used to cross validate them. Finally, the neural network will be tested with actual data gathered from the CEB.

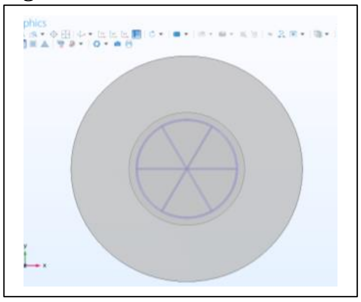

Figure 4 **Figure 5**

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