Determining accelerated aging power cable spatial temperature profiles using Artificial Neural Networks

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***Abstract*- The spatial temperature profile of Medium-Voltage (MV) extruded power cable, undergoing accelerated aging in a tank filled with water according to IEEE standard 1407 guidance, is estimated by combining Finite-Element Modelling (FEM) and an Artificial Neural Network (ANN). ANSYS Fluent is first used to establish a 3-D finite-element model and to simulate the temperature distribution within the power cable. In order to estimate temperature at any position within the power cable thus informing a more accurate aging model based on the variation temperature with position, a 3 layers ANN, trained by Bayesian regularization back-propagation is then developed. For the ANN, the FEA simulation temperature profiles at specified nodes are used as the input information. The resulting model is useful to understand how each position within a cable undergoing artificial aging is affected by different temperatures.**

I. Introduction

Medium Voltage (MV) extruded electric power cables are widely utilized in power transmission and distribution systems. Aging of cable insulation material may cause power failures which are dangerous for operators and incur cable replacement costs. Insulation power cables can be artificially aged through the synergistic impact of high voltage and high temperature in a heated water environment. In order to achieve consistency between aging tests the IEEE published Standard 1407 to provide guidelines of accelerated aging experiments for MV extruded power cables using water-filled tanks [1].

The cables in the standard are heated up by joule loss heating in the conductor which is produced by applying current to cable conductors. In IEEE Std1407, the temperature distribution across the cable length and in the water tank is supposed uniform therefore a dummy cable sample is used for temperature monitoring.

Temperature plays a notable role in accelerated aging processes of power cable insulation. In this respect the Arrhenius equation is an analytical chemical model that can be used for estimating the thermal degradation of cable insulation materials caused be elevated temperature. Using this model the lifetime (τ) of insulation material will be reduced with temperature variation based on (1):

$$\tau = B * exp\ (E_a/k_B T) \quad (1)$$

where E_a is activation energy (J), k_B is the Boltzmann constant (1.38×10^{-23} J/K), T is absolute temperature in K and B is a constant obtained from experimental tests.

Equation (1) can be represented as an empirical law where the lifetime is halved when the aging temperature increases by 10^0C. Therefore, an understanding of temperature profile at any cable insulation position will provide helpful information for researching general cable aging accelerated processes.

In this paper, the simulation of single loop cable in an accelerated aging water-filled tank is constructed using Finite Element Analysis (FEA). The model is divided into a number of small size elements to perform the calculations based on mathematical models of thermal conduction and natural water convection. The temperature at specified mesh points can be extracted from the simulation results. However, the temperatures across the general cable structure between mesh points are not directly evaluated from the simulation results.

An Artificial Neural Network (ANN) is thus utilized to estimate the more detailed temperature profiles across the cable structure. Due to the existence of natural water convection in a tank, the relationship between specific points within the cable and the associated temperatures is non-linear and complex. Compared to interpolation polynomial methods that could be used, ANNs have the potential to provide higher computational power and improved efficiency in determining cable insulation temperature profiles at any selected position.

In this paper, the ANN is therefore constructed to provide a temperature profile prediction tool, converting the output temperatures of the simulation model into an accurate spatial temperature evaluation for all points within the cable insulation.

II. ANSYS Model and Simulation of Temperature Distribution

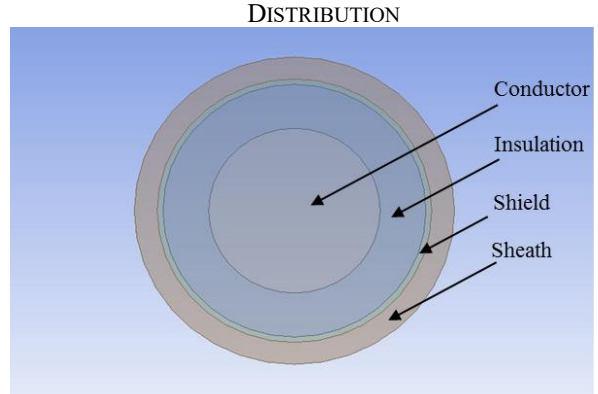

Fig. 1. Cable model in ANSYS for thermal simulation according to IEEE Std1407

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TABLE I
DIMENSIONS AND MATERALS OF CABLE MODEL

Layer	Diameter	Material
Conductor	15mm	Aluminum
Insulation	23mm	XLPE
Metal shield	24mm	Copper
Outer sheath	28mm	MDPE

A. *Simulation Modelling and Meshing*

A 3-D finite-elements model of the power cable thermal aging in a chamber filled with water was constructed in ANSYS Fluent based on IEEE Std1407.The transient heat transfer equation in the solid regions and fluid region are employed within ANSYS. Buoyancy-driven flows, also known as natural-convection flows are modeled by ANSYS Fluent.

The dimensions of a practical extruded MV power cable dimensions were referred to for constructing the cable model in the simulation and are shown as Fig.1. The effect of thin semi-con layers (thickness around 0.3mm) on the temperature distribution in the power cable is small enough to be neglected, so there are four main layers in the power cable model, namely conductor, insulation, metal shield and outer sheath. The material and diameter of each layer is shown as Table I, the material for insulation is Cross-linked Polyethylene (XLPE), and the material for outer sheath is Medium-Density Polyethylene (MDPE).

In order to reduce the simulation time while keeping a high number of computational nodes for numerical accuracy, a model of only a single cable loop in a water-filled tank was constructed. Following IEEE Std1407, the model, including a tank filled with water and a cable loop is shown as Fig.2. The tank dimensions are also shown in Fig.2. In this model, the diameter of the cable loop is 700mm, the cable loop is located in the middle of the tank, and the straight-ended elements of the loop extend out of tank in contact with air to simulate the practical experimental connection points for a power supply. The length of power cable is 4.5m. The constructed model including the cable, tank and the fluid domain was meshed into 40601279 elements in the FEA simulation, for which the insulation layer comprises 6487404 nodes.

B. *Simulation Set up*

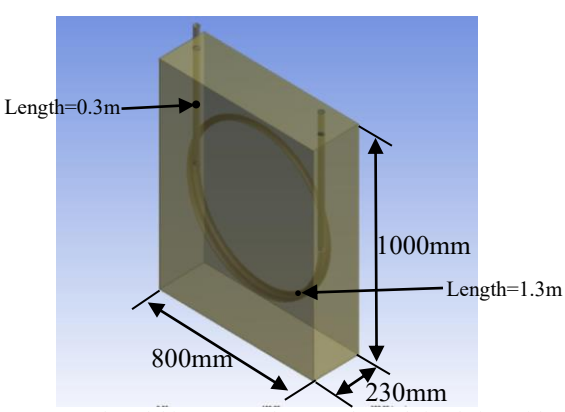

Fig. 2. Constructed model in ANSYS for FEA thermal simulation with tank dimension and cable length

TABLE II
THERMAL PROPERTIES OF XLPE AND MDPE CHANGING WITH TEMPERATURE

Material	Temperature (^{0}C)	Thermal conductivity (W/m-k)	Specific heat (J/kg- K)
XLPE	20	0.223	2034
	50	0.267	2976
	90	0.28	4049
MDPE	20	0.4	1916
	50	0.48	2300

Previous research has shown that the thermal properties of the insulation material and the outer sheath material varies with temperature and has a considerable influence on cable thermal conduction [2]. Thus, the XLPE and MDPE materials used in the simulation have thermal conductivity and specific heat capacities which change with temperature as shown in Table II.

The Boussinesq approximation is applied to the flow of water in the tank, which states that the fluid density variation is only important in the buoyancy term. The reference density of water is 998 kg/m^3 at 20^{0}C, and the thermal expansion coefficient of water is 0.000216 (1/K). The acceleration due to gravity in the model is set as 9.81m/s^2. The ambient environment around the tank is air at 20^{0}C and the boundaries of the tank walls and the cable in air are given convection coefficients (h) as shown in Table III.

As the resistive heating of the conductor provides the main source of thermal stress for MV power cables [3], in this research, the cable conductor is regarded as a heat source volume with a power density to simulate resistive losses in the conductor. The insulation, metal shield and outer sheath layers are regions with no heat source.

In the IEEE Std1407, the temperature of water in the tank is required to be controlled at around 50^{0}C, so the initial temperature of water and cable in the tank is set as 50^{0}C in the FEA. The maximum core temperature of power cables required to be heated up to around 90^{0}C in approximately 20 min, thus the power density of the cable conductor in the simulation is 8.5×10^5W/m^3 over the first 20 min. This temperature is maintained for 8 hours as per IEEE Std1407, so the power density of the cable conductor in the simulation decreases to 5.5×10^5W/m^3 during this period to ensure constant temperature. This power density was determined through trial and error in the simulations. The water temperature over the first 8 hours in the simulation does not above 52^{0}C as per standard. After 8 hours, the power density of power cable conductor is set to zero to simulate cooling down of the power cable within practical working cycle conditions.

C. *Simulation Results*

The transient thermal simulation was implemented to investigate the cable temperature distribution over the 1st hour. The resulting simulated temperature distribution on the cable conductor surface along the cable length is shown in Fig.3 (a).

TABLE III
CONVECTION COEFFICIENT OF MODEL BOUNDARIES CONTACTING WITH AMBIENT

Boundaries	Tank upward wall	Tank downward wall	Tank side walls	Cable surface
Value of h	7 W/m^2 -k	3 W/m^2 –k	5 W/m^2 -k	10 W/m^2 -k

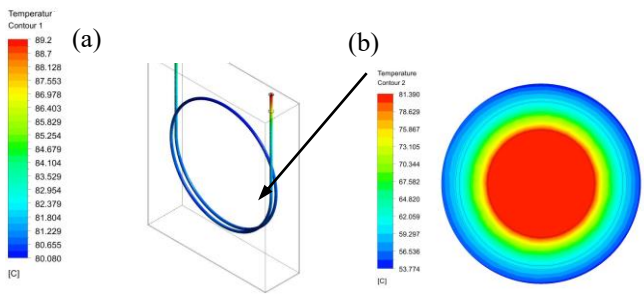

Fig.3. (a) FEA simulation results of 1st hour temperature distribution on cable conductor surface and (b) temperature cross-section of cable selected location

It is seen from the Fig. 3(a) that the temperature profile at the cable conductor surface is non-uniform along the cable length. The maximum temperature (around 90^0C) was observed where the cables were exposed to air at both terminals of the cable loop. The temperature of the conductor surface decreases gradually with distance from the two cable ends, with the middle part of the cable conductor surface having a temperature of around 80^0C.

The arrow in Fig.3 (a) shows the location of the selected plane for Fig. 3 (b).The temperature distribution across the cable cross-section is shown in Fig. 3 (b). It can also be observed that there is a significant temperature decrease from the cable core (around 80^0C) to the cable outer surface (around 54^0C).

III. Artifical Neural Network Model

An ANN is then employed to estimate the temperature profile at any position within the cable based on the data acquired from the FEA simulation results.

A. Construction and Training of ANN

The flow chart for constructing the temperature estimation ANN model is shown as Fig. 4. The first step is to model the flow of heat in the experimental system- as described in section II. Extracting the temperature profile from the simulation outputs is the second stage. In order to make the input and output of the ANN model linear and improve the model prediction efficiency, the data is then pre-processed in MABLAB, converting the temperature profile (T) from an original Cartesian coordinate system of the cable (x,y,z) to a Cylindrical coordinate system (r,θ,l),

where, r is the radius from cable center (m), θ is angle, l is the position along the length of cable (m) and T is temperature (K).

The architecture of developed the ANN shown in Fig.5. There are 3 layers in the ANN: an input layer, a hidden layer with 10 neurons and an output layer. After data pre-processing, the data location profile (r,θ,l) is the input vector into the ANN with the T is the ANN output.

70% of the processed data obtained from the simulation is selected for training the ANN, 15% is used for validation and the final 15% is used for testing.

In order to create a reliable ANN model, selection of a suitable training function is critical. In this paper, the training function used in the hidden layer of the ANN is a Bayesian regularization back-propagation algorithm.

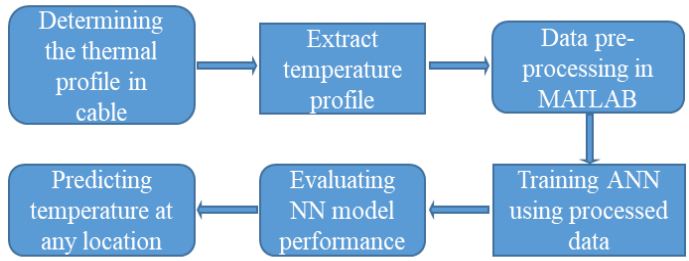

Fig.4. Flow chart of constructing a temperature estimation ANN

Backpropagation algorithms are commonly used for training ANN [4]. They perform three steps: 1. forward propagating the input values into the hidden layer; 2. back propagating the sensitivities to reduce the error; and 3. updating the weights.

In the training process, a common performance function (F) is the mean sum of square of Neural Network errors (E_D) as shown in (2) is used for calculating the discrepancy between target values and predicted values:

$$F=E_D= (1/N)\Sigma_1^N(t_i'-t_i)^2 \qquad (2)$$

In (2), N is the number of samples in the database, t_i' is the estimated value and t_i is the target value.

The disadvantages of some backpropagation algorithms are slow convergence rate and problems with overfitting. Some regularization methods have been developed to overcome the overfitting problems. Among regularization methods, Bayesian regularization not only obtains lower mean squared errors [5], it also linearly combines the sum of squares of weights (E_w) and squared errors to minimize the target function (2) by using equation (3) so that the trained network has good generalization qualities[6]:

$$F=\beta E_D+\alpha E_w \qquad (3)$$

Here, α and β are regularization parameters which need to be optimized. A Bayesian regularization method is applied to automatically obtain the optimal regulation parameters.

B. Performance of ANN

The mean square error (MSE) as shown in (2), and Pearson correlation coefficient (R) are used to evaluate the performance of the ANN model. R is an essential index of regression analysis which indicates the correlation between the predicted results and the target outputs. The range of R is between -1 and 1, while with an absolute value of R closer to 1, the better the model performs [7].

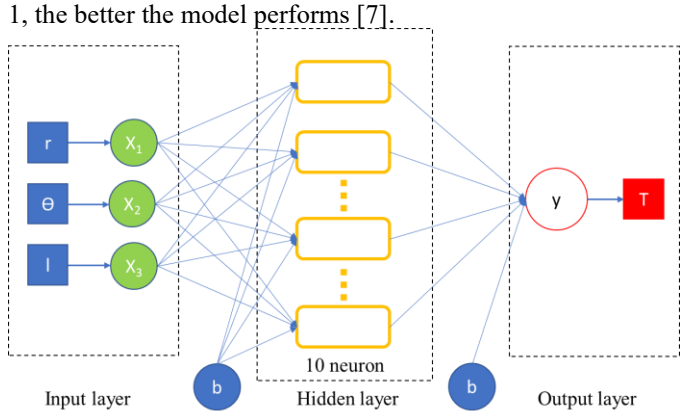

Fig.5. Architecture of constructed ANN

The ANN model is trained for 1000 iterations (also called epochs). The MSE variation with ANN training epochs is shown as Fig.6. The smallest MSE of the model is 0.056 at epoch 1000, but the performance improvement of the model after 400 iterations is not obvious. The R values related to training set and test set are shown as Fig.7, both of the training set and the test set with R values are very close to 1.

C. *Application of ANN*

The power cable from 0.3m to 1.3m is selected from the simulation model, and illustrated in Fig.2, to demonstrate a comparison of the original temperature profile from FEA results and estimated temperature profile from the ANN.

The cable insulation temperature profile from FEA results in cylindrical-coordinates is shown as Fig.8, where the color bar represents the temperature value in Kelvin. The temperature is represented by Kelvin scale so as to help predicting the cable lifetime by Arrhenius Model. Smaller radius insulation positions have significantly higher temperature due to being closer to the cable core. However, there are many points where no temperature has been evaluated especially in the radius dimension as no mesh node exist at these positions. Fig. 9 represents the cable insulation temperature profile for the same cable length as predicted by the ANN in cylindrical-coordinates, where the temperature at any point is now estimated by the ANN model.

IV. Conclusion

For accelerated aging of power cable in a water tank environment, it is demonstrated that the application of an ANN allows the effective prediction of the temperature profile across all positions in the power cable based on a limited FEA simulation of the conditions.

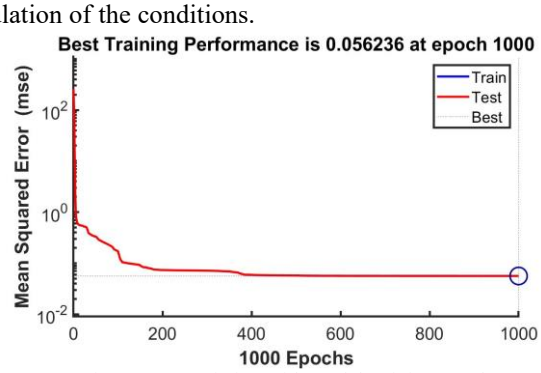

Fig.6. MSE variation with model training epoch

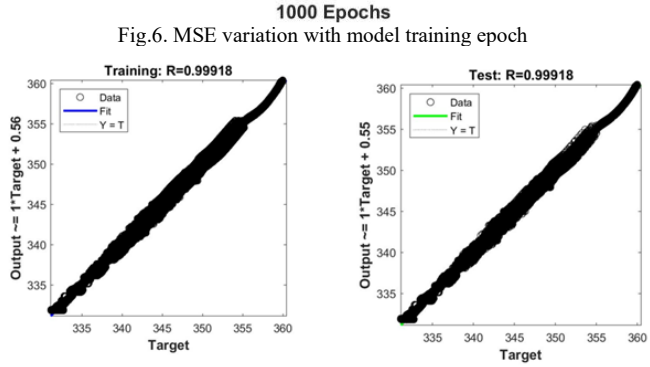

Fig.7. R of training set (right hand side) and test set (left hand side)

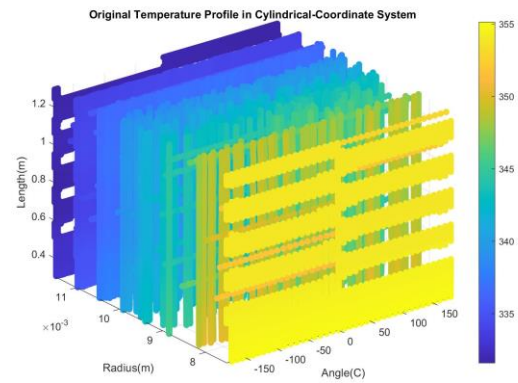

Fig.8. Temperature profile of insulation from FEA simulation results in Cylindrical-coordinate system

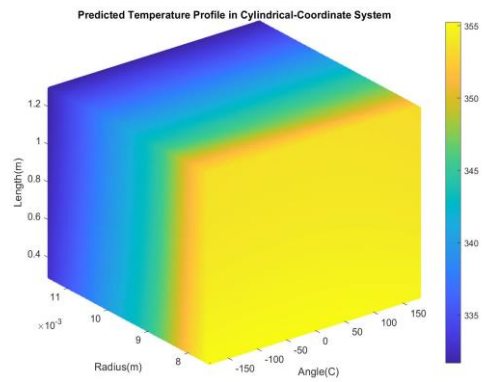

Fig.9. Temperature profile of insulation predicted by ANN in Cylindrical-coordinate system

The ANN enables a more informative analytical model to extract temperature at any cable position to compliment future effective cable bulk ageing calculations for such scenarios. The work will also complement practical temperature measurements and enable improved understanding of temperature profiles and gradients across cable undergoing accelerated aging.

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