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Experimental and predicted XLPE cable insulation properties under UV radiation

Abdallah HEDIR[1,*], **Ali BECHOUCHE**[2], **Mustapha MOUDOUD**[1], **Madjid TEGUAR**[3], **Omar LAMROUS**[4], **Sébastien RONDOT**[5]

[1]LATAGE Laboratory, Mouloud Mammeri University, Tizi-Ouzou, Algeria
[2]L2CSP Laboratory, Mouloud Mammeri University, Tizi-Ouzou, Algeria
[3]LRE Laboratory, Ecole Nationale Polytechnique, Algiers, Algeria
[4]LPCQ Laboratory, Mouloud Mammeri University, Tizi-Ouzou, Algeria
[5]LISM Laboratory, UFR Sciences, Reims, France

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Abstract: This paper deals with the behavior of the crosslinked polyethylene (XLPE) used as high-voltage power cable insulation under ultraviolet (UV) radiations. For this, XLPE samples have been irradiated for 240 h using low-pressure vapor fluorescent lamps. Electrical (surface and volume resistivities), mechanical (tensile strength, elongation at break and surface hardness) and physical (weight loss, water absorption, work of water adhesion and contact angle) tests have been first carried out. Experimental results show that the XLPE characteristics are affected by UV radiation. Indeed, a decline in surface resistivity, mechanical properties, and contact angle, and an increase in the water retention amount and weight loss have been recorded. In order to predict and extrapolate some XLPE properties, a supervised artificial neural network (ANN) trained by Levenberg–Marquardt algorithm has been designed. The collected database is used to train and test the ANN performance. The obtained results show that the proposed ANN algorithm presents good estimation and prediction since the predicted output values agree with the experimental data.

Key words: Crosslinked polyethylene, ultraviolet, cable, insulation, artificial neural network, Levenberg–Marquardt

1. Introduction

Polymer materials are increasingly used for insulation in electric distribution systems. Over the past few decades, the traditional insulating materials, such as the impregnated paper, have been replaced by polymeric materials, especially polyethylenes [1, 2]. Due to their excellent properties and low cost, polyethylenes are widely used in industrial applications as power cable insulation [3].

In the last decade, crosslinked polyethylene (XLPE) is the commonly used insulation material in power cables and cable accessories [4]. Due to its excellent electrical properties [5] and high operating temperature compared to the original polymer, namely low-density polyethylene [6], XLPE has gradually replaced other polyethylenes. The manufacturing technology of medium- and high-voltage cables uses several materials around the conductive core. The XLPE layer is often an intermediate insulation, but in some cases, it may be an external one. Like all polymers, XLPE insulating material may operate under severe service conditions such as heat, radiations, electrical and mechanical stresses, and so on. Such constraints cause irreversible damages to the insulation leading to the dielectric strength reduction of such material [7]. Given the great importance of

*Correspondence: abdallahhedir@yahoo.fr

this insulation material, different experimental studies have been recently devoted to analyzing the behavior of the XLPE insulating material under various stresses [8, 9]. On the other hand, several investigations have been conducted to study the performance of the XLPE insulation on service conditions. Liu et al. [10] studied the growth of electrical trees in XLPE cable insulation under DC voltage. Gu et al. [11] investigated the feasibility of discovering the defects by PD testing under DC voltage. Ouyang et al. [12] studied the influence of thermo-oxidative aging on the space charge distribution of XLPE cable insulation.

For a relatively long period, radiations have been considered as one of the most destructive constraints [13]. Thus, under radiations, XLPE cable insulation and cable accessories properties may change [14, 15]. In consequence, the insulation quality will be affected. Aljoumaa and Ajji [16] investigated the effect of gamma irradiation on the XLPE cable insulation. The study of Sugimoto et al.[17] focused on the degradation mechanisms of XLPE insulation under thermal and radiation aging. Shimada et al. [15] indicated that gamma radiation induces changes in the structural and mechanical characteristics of XLPE insulated cables used in nuclear power plants. Nowadays, studies investigating the UV radiation influence on XLPE insulator are scarce, and the underlying mechanisms are still unclear. Therefore, it is useful to study the underlying degradation mechanism induced by this constraint.

Actually, it is well known that experimental studies are often costly and time-consuming [18]. To overcome such difficulties, many researchers developed artificial intelligence approaches to predict insulating material behavior under several constraints [19]. Among these techniques, artificial neural network (ANN) is one of the most widely used approaches. Due to their numerous capabilities such as self-learning and self-organization, various types of ANNs are applied [20, 21]. Neural networks particularly depend on their architectures and training algorithms. The most common type is the multilayer perceptron (MLP) network trained by a backpropagation algorithm. In this ANN, known by â fully connectedâ , every neuron in the previous layer is connected to every neuron in the next layer [22]. This ANN is constituted by a set of processing units, also known as neurons, which are arranged in a layered structure.

In recent studies, ANNs have been used as a powerful tool to predict and diagnose electrical systems, especially high voltage insulation materials [23]. Khan and Koo [24] used an MLP to diagnose partial discharge defect patterns of XLPE-insulated cable under DC stress. Santosh et al. [7] proposed an integrated framework based on ANNs to predict the reliability of XLPE insulated electrical cable. ANNs have been also used to prevent electroshock risk and XLPE insulation faults in high voltage underground cable lines [25]. Mohanty and Ghosh [26] proposed two ANNs to predict the PD breakdown voltage of solid insulating materials under AC conditions. Boukezzi et al. [27] developed an ANN approach to predict mechanical properties of XLPE insulated cables under thermal aging.

Our present study aims to analyze the impact of the UV radiation on the behavior of XLPE power cable insulation; this impact had never been studied before 2016 since when we have been the sole research team which has developed, until now, two experimental investigations on this subject [28, 29]. Dielectric characterization (based on dielectric constant, dissipation factor, dielectric loss index, and AC volume resistivity), visual observation (color change) and SEM analysis have been performed in the first work. For more investigation in XLPE aging process under UV exposure, mechanical (consisting in tensile strength and elongation at break) and physical (contact angle and water retention) characteristics have been examined in the second work. As additional analysis, fourier transform infrared spectroscopy has been also performed.

This paper is a continuation of the two previous studies. It contains two distinct parts; experimental study followed by a prediction using artificial intelligence technique. Indeed, to analyze the XLPE photo-degradation phenomenon, experimental tests, including electrical measurements, mechanical characterization and physical experiments have been carried out by irradiating XLPE samples for 240 h using low-pressure vapor fluorescent lamps. The electrical characteristics consist of the surface and the volume resistivities. The mechanical ones concern the tensile strength, the elongation at break, and surface hardness. The physical tests have been performed to study the XLPE samples surface hydrophobic properties. For this, weight loss, water absorption, work of water adhesion, and contact angle have been analyzed. As the second part, a supervised ANN is introduced to predict some XLPE properties exceeding largely the experimental ones. To achieve this objective, an MLP network trained by a backpropagation algorithm, namely Levenberg–Marquardt, is developed. To train and test the neural network performances, the collected database obtained from experiments is used. Predicted results are then compared to the experimental ones to evaluate the MLP ability for predicting the evolution of XLPE properties.

This paper is organized as follows: Section 2 briefly explains the experimental setup. Section 3 presents the architecture of the developed ANN. Section 4 illustrates the experimental and computational results. Finally, Section 5 draws the conclusion.

2. Experimental arrangements

The electrical, mechanical, and physical experiments have been carried out at the LATAGE laboratory of Mouloud Mammeri University. The main objective is to analyze the behavior of the XLPE insulation cable samples aged under UV radiations.

2.1. Materials

The behavior of the commercial XLPE BOREALIS HFDE LE4201R, used in medium- and high-voltage cable insulation, has been studied in this investigation. The polyethylene in its granulating form is blended with 2% of dicumyl peroxide. Square plates of 130 mm $\times$ 130 mm and 2 ± 0.2 mm thickness have been molded at 180° C under a pressure of 300 bars using pressurized heat press. Depending on the nature of tests, samples in different forms are then cut from the obtained plates.

2.2. UV exposure

The accelerated UV aging has been carried out in a UV-CURE chamber. The XLPE samples were irradiated for 240 h by eight low-pressure vapor fluorescent lamps (Phillips Actinic BL TL-DK - 36W/10 1SL), of 36 W and wavelength radiations ranging from 350 nm to 400 nm. The lamps have been placed at a distance of 10 cm from each XLPE sample surface. The electrical, mechanical, and physical measurements have been done after each 20 h of UV exposure.

2.3. Electrical measurements

The DC electrical resistances of the XLPE samples have been calculated from the slope of the applied voltage/current (V/I) characteristic which is measured using an automated Hewlett–Packard 4140B picoammeter/voltage source. For this, five samples have been used for each exposure time.

DC volume and surface resistivities were determined using a measurement cell (three electrodes method) by applying voltage ranging between –1 and +50 V. The electrical resistivities of the XLPE were calculated using the resistance values. The resistivities are related to the configurations and dimensions of the used electrodes. DC volume resistivity ρ_V is obtained from the formula:

$$\rho_V = (S/e).R, \tag{1}$$

where R is the measured resistance in ohm, S is the sample surface, and e is the sample thickness.

Surface resistivity ρ_S is calculated by:

$$\rho_S = (P/g).R, \tag{2}$$

where R is the measured resistance in ohm, P is the effective perimeter $(P = (\pi(D_1 + D_2))/2)$ of the guarded electrode, $g(= (D_1 - D_2)/2)$ is the distance between the guarded and the ring electrode.

2.4. Mechanical characterization

According to the IEC 600811.1.1 standard [29], XLPE samples with dumbbell shape of 5 cm length were used for tensile (elongation at break and tensile strength) and surface hardness tests. For this purpose, seven samples are used.The first five were intended for testing the elongation at break and the tensile strength. The two others were reserved for measuring the surface hardness. The tensile testing consist of breaking the sample using a Schnek-Trebel testing machine, at ambient temperature, using a dynamometer operating at a cross-head speed of 50 mm/min. The elongation at break and the tensile strength were measured simultaneously. Surface hardness measurement was performed using an Amsler hardness tester.

2.5. Physical experiments

The samples in the square form of 6 cm × 6 cm were used for physical tests. After each 20 h of UV exposure, ten samples were taken from the UV irradiation chamber. The first five were intended for measuring the weight loss, the contact angle, and the work of water adhesion. The others were used for evaluating the water absorption. The contact angle θ_W corresponds to the angle formed by a droplet of 10 mL of distilled water with the XLPE sample surface. It was measured before and after UV exposure.

The work of water adhesion W_A related to the measured contact angle is given by the following equation:

$$W_A = \gamma_W(1 + cos(\theta_W)), \tag{3}$$

where γ_W is the surface tension of water [30] and θ_W is the contact angle. The amount of retained water is obtained by calculating the samples' weights before and after drying. The water absorption is calculated using the formula:

$$W_r = ((W_2 - W_1)/W_1).100, \tag{4}$$

where W_2 and W_1 are respectively, the mass of wet and dry sample.

The loss in mass W_L is obtained by weighing the samples before UV aging and immediately after their removing from the aging chamber. The weight loss is given by the equation below:

$$W_L = ((W_i - W_f)/W_i).100, \tag{5}$$

where W_i and W_f are the initial and the final mass, respectively.

3. Prediction network for XLPE sample properties

In order to predict XLPE sample properties, a three-layer network with a sigmoid transfer function is developed under Matlab/Simulink environment. The architecture of this ANN is depicted in Figure 1. In this ANN, the exposure time is used as inputs. The estimated outputs are compared to the measured ones. Therefore, the obtained estimated progression error is also used as a second input to update the weights.

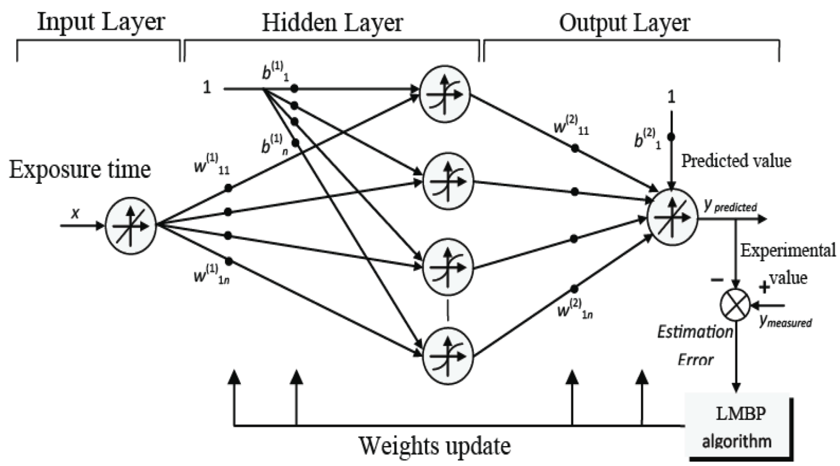

Figure 1. The proposed MLP model for predicting XLPE insulation properties.

Considered as one of the most famous algorithms, Levenberg–Marquardt back propagation (LMBP) is selected for training the MLP. Back propagation (BP) is a gradient descent algorithm used to minimize the estimation error of the ANN during training in the case of particular nonlinear system. BP follows the Widrow–Hoff learning rule [31]. Matlab simulink tool is used to design the suggested ANN.

Moreover, the *trainlm* instruction is used as a network training function that updates weight and bias values according to LMBP optimization algorithm.

According to Figure 1, the output of the used sigmoid activation function is given by:

$$y(n) = \frac{a}{1 + e^{\gamma v_j(n)}} + c, \tag{6}$$

where a, c, and γ are the parameters allowing to obtain symmetric or asymmetric functions with different profiles [32] and $v_j(n)$ is the neuron activity.

During the training prosses, the weight matrix is updated as follows:

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n+1). \tag{7}$$

The change in the weight matrix $\Delta w_{ij}(n+1)$ is given by the general expression:

$$\Delta w_{ij}(n+1) = \eta \delta_j(n) x_i(n), \tag{8}$$

where η is the learning rate which has a positive value less than 1, δ_j is the neuron j input error, and x_i is the neuron i input. The parameter values and the activation functions used in the ANN network are depicted in Table 1. As shown in Figure 1, the obtained ANN has the following architecture: One linear neuron in the input layer, variable tan-sigmoid neurons in the hidden layer, and one linear neuron in the output layer. In order to select the best network architecture, the number of neurons in the hidden layer was varied from 10 to 35. It should be noted that the best prediction results are obtained in this range (10–35).

Table 1. Values of parameters and activation functions used in the neural network model.

	Input layer	Hidden layer	Output layer
Activation function	Linear	Symetric sigmoid	Linear
parameter -γ	-	2.0	-
parameter -a	-	2.0	-
parameter -c	-	–1.0	-
Number of neurons	1	10-35	1
Learning rate η	0.05		
Number of inputs	1		
Number of outputs	1		
Final error	< 5E-6		

4. Results and discussion

The experimental results and the predicted ones, presenting the evolution of the different XLPE properties as a function of exposure time are given in Figures 2–4. About 40% of the data of each property have been used to train the network; the learning time is about 100 h, which correspond to five experimental measurements. The remaining data (60%) corresponding to 140 h of aging has been reserved to test the neural network. The relative maximum errors are presented in Table 2.

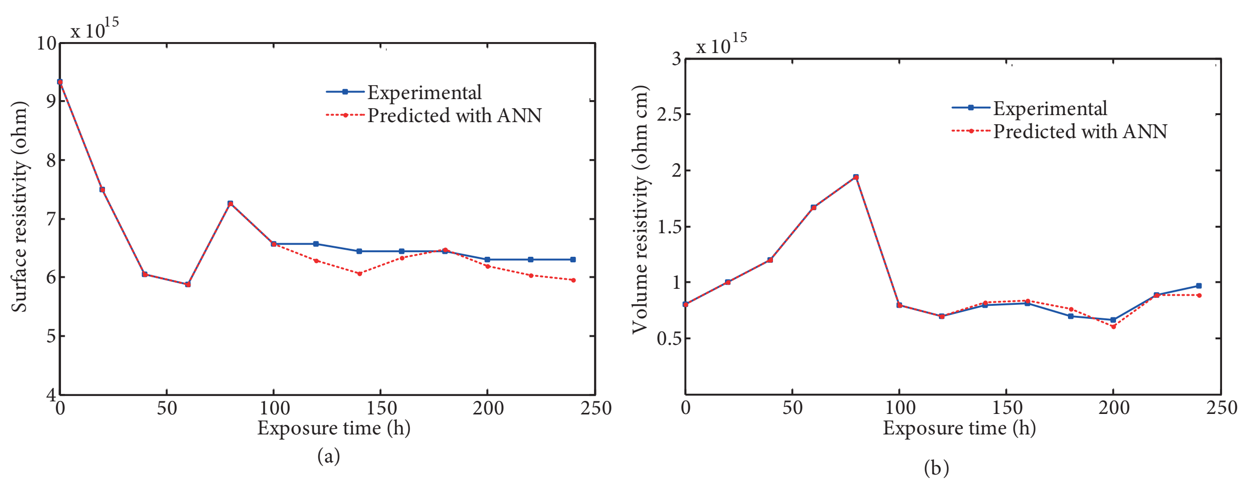

Figure 2. Experimental and predicted resistivities according to aging time, (a) DC surface resistivity and (b) DC volume resistivity.

4.1. Electrical resistivities

Characteristics (a) and (b) of Figure 2 display respectively the surface and the volume electrical resistivities evolutions under UV radiations.

For experimental tests, Figure 2a shows that the surface resistivity variation is not monotonic; it has a tendency to decrease with appearance of a main peak after 80 h of exposure, where the resistivity reaches the

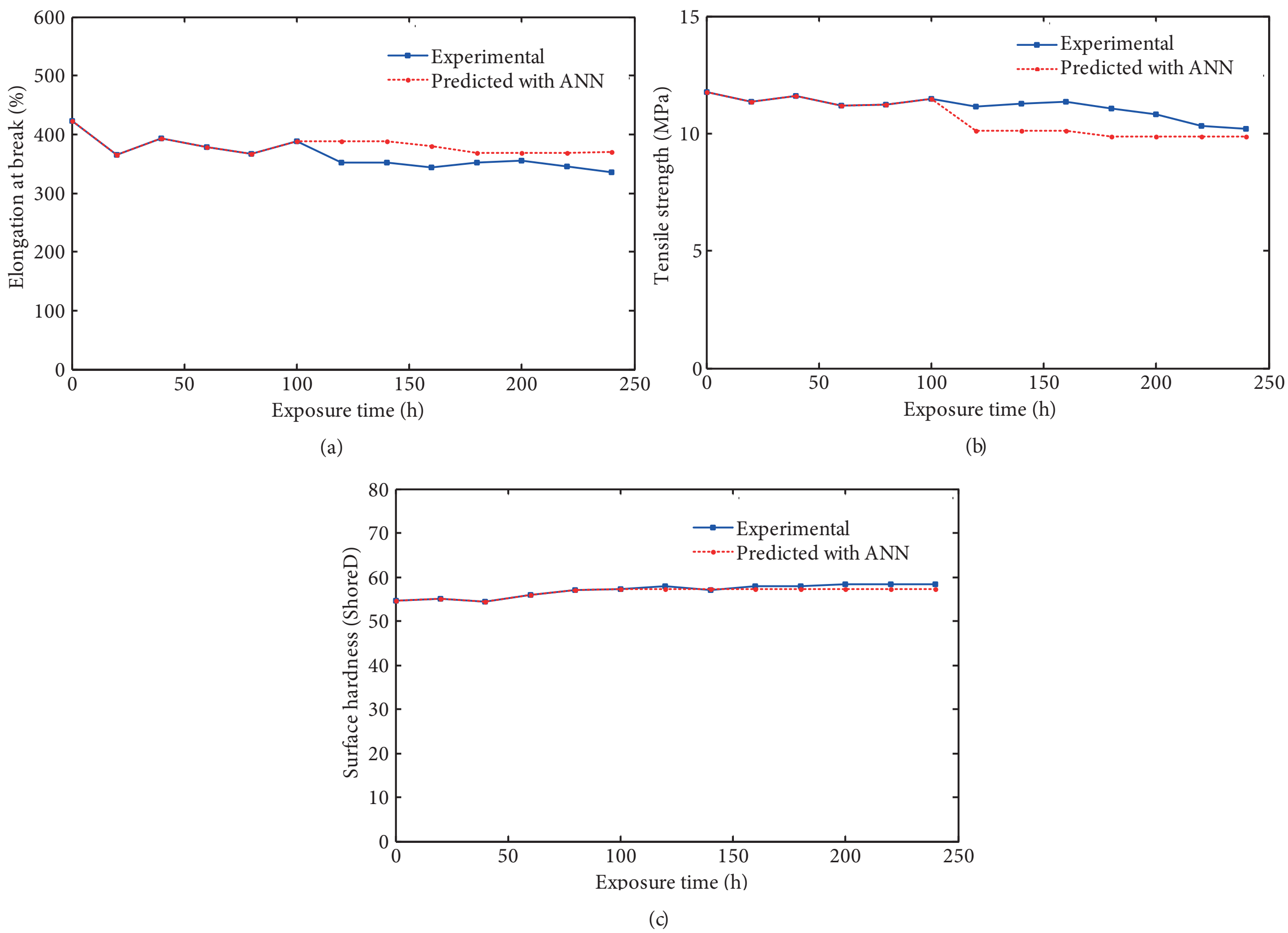

Figure 3. Experimental and predicted mechanical properties according to aging time, (a) elongation at break, (b) tensile strength, and (c) surface hardness.

value of $7.25 \times 10^{15}\Omega$. This peak can be attributed to the low molecular weights (LMWs) migration caused by UV. These LMWs further reinforce the insulating character of the polymer from electrodes and cause an increase in surface resistivity [33]. Generally, superficial conductivity increase due to the surface material deterioration can be related to the hydrophilicity augmentation induced by photo-oxidation [34].

From Figure 2b, experimental DC volume resistivity is not considerably affected by ultraviolet radiation. However, a slight rise has been recorded when volume resistivity increases from about $8.08 \times 10^{14}\Omega$ cm at the beginning of UV exposure and reaches the value $9.7 \times 10^{14}\Omega$ cm after 240 h of exposure. The experimental results show that the insulation material keeps its electrical conductivity performance intact.

For the predicted surface and volume resistivities, the learning time is 100 h and the prediction one is 140 h. The obtained results indicate that the used MLP is a good prediction neural network and presents acceptable errors. As shown in Table 2, the relative maximum error ranges from 0.5% to 5.67% for surface resistivity and from 0.52% to 8.55% for volume resistivity.

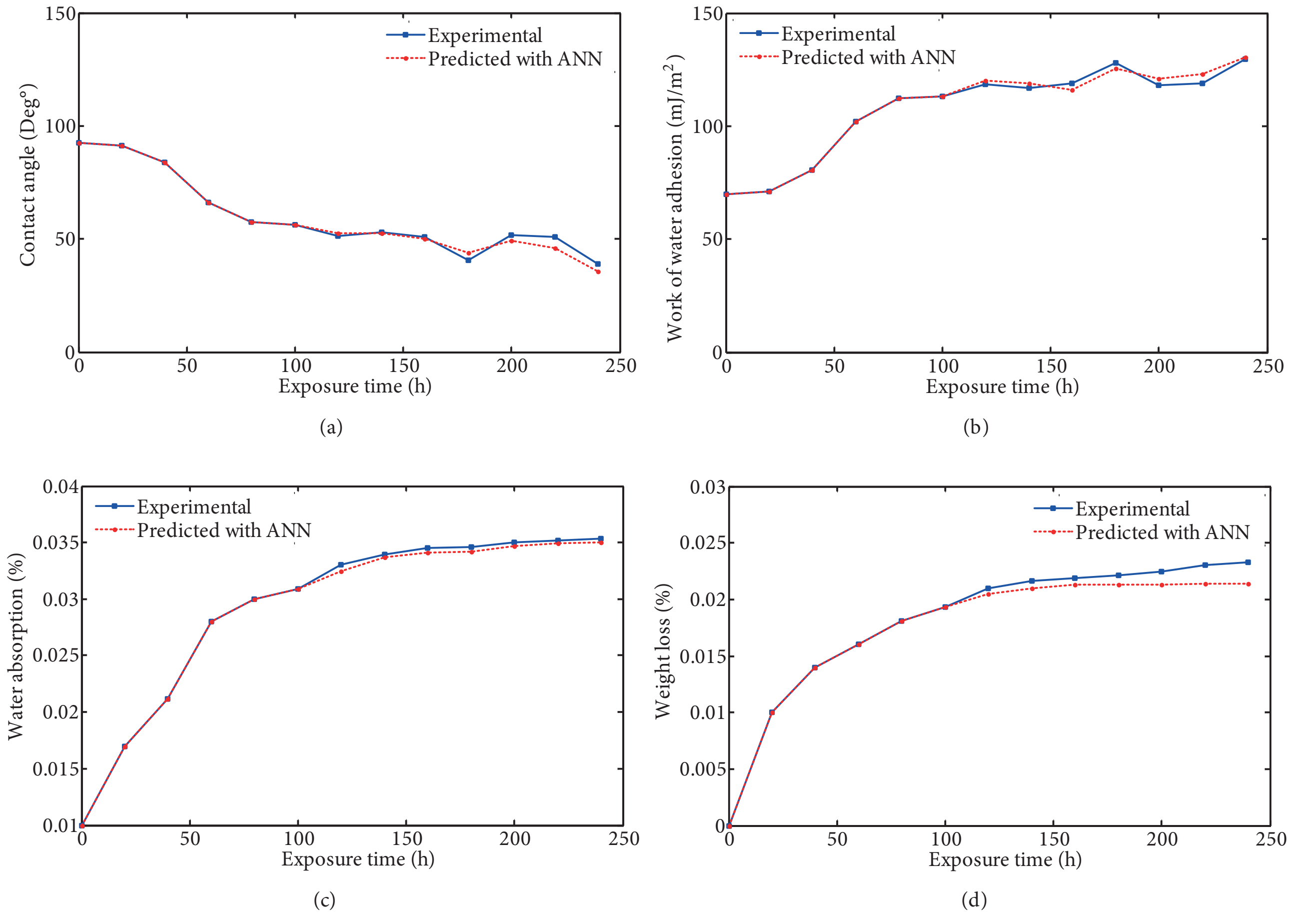

Figure 4. Experimental and predicted physical properties according to aging time: (a) contact angle, (b) work of water adhesion, (c) water absorption, and (d) weight loss.

Table 2. Relative maximum errors of properties prediction in %.

Exposure time (h)	Surface resistivity	Volume resistivity	Elongation at break	Tensile strength	Surface hardness	Contact angle	Work of water adhesion	Water absorption	Weight loss
120	4.29	0.52	9.94	9.41	1.10	2.10	1.43	1.51	2.38
140	5.67	2.43	9.94	10.38	0.63	0.49	1.88	0.82	2.77
160	1.66	3.73	10.57	10.93	1.10	1.61	3.36	2.60	2.73
180	0.5	8.55	4.71	10.49	1.10	7.90	0.78	1.15	3.61
200	1.65	8.4	3.7	8.67	1.66	4.45	2.54	0.85	5.33
220	4.08	0.6	6.73	4.16	1.67	9.47	3.45	0.86	6.95
240	5.29	8.24	10.11	3.03	1.70	8.63	0.77	0.88	8.15

4.2. Mechanical properties

Curves (a) and (b) of Figure 3 depict, respectively, the elongation at break and tensile strength evolutions. From experimental characteristics, the mechanical properties of XLPE insulation decrease slightly with UV-exposure time. According to the literature [35, 36], the observed change can be attributed to the XLPE insulation photo-degradation which induces chemical alterations. These alterations lead to the decrease of both amorphous region size and molecular weight, engendering the weakness and embrittlement of the material, responsible for the decrease in the elongation at break and tensile strength.

Figure 3c represents the XLPE insulation hardness evolution. The surface hardness obtained from experiments increases slightly. It grows from 54 shD to 58 shD after 100 h of UV-exposure and remains practically constant after this period. The obtained results may be attributed to the phenomena of crosslinking and/or end-linking which can affect the XLPE insulation mechanical properties [29].

The back-propagation neural network has been applied for predicting the XLPE mechanical properties. Considering the results shown in Figure 3, the MLP predictions are in good agreement with experimental results, since the predicted values are close to the experimental ones. The maximal relative error for the elongation at break is about 10.57%, against 10.93% for the tensile strength. The prediction quality in the case of surface hardness is better than the previous mechanical properties; it does not exceed 1.7%.

4.3. Physical characteristics

The contact angle, the work of water adhesion, the water absorption, and weight loss evolutions are plotted as function of aging time in Figures 4a–4d, respectively.

The experimental characteristic of Figure 4a shows that the contact angle decreases dramatically from 92.4° to 54.3° in the first 120 h of exposure time. The contact angle reaches its minimal value of 38.88° at the end of the test. The contact angle decrease can be assigned to the creation of new polar groups [37], to surface morphology changes (increase of surface roughness), and to the creation of carbonâ oxygen groups [38].

As shown in Figure 4b, work of water adhesion is in correlation with the decrease in hydrophobicity (decrease in contact angle). This behavior can be attributed to the photo-oxidation phenomenon which leads to the increase of surface free energy and polar content [29].

From experimental values of Figure 4c, the water absorption increases rapidly at the beginning of treatment. Thus, after 80 h, water uptake reaches 0.03%. After that, the absorption process inside the XLPE insulation becomes less important. This behavior can be attributed to the increase and to the formation of chemical structures with high polarity as a result of photo-oxidation processes [39].

The experimental curve of Figure 4d illustrates that UV radiations induce a weight loss in XLPE samples. This weight loss can be attributed to the evaporation, during photo-degradation, of volatile compounds present in the material surface. Using TGA Analysis, Liu et al. [40] showed that weight loss can be induced by the evaporation of low molecular weight species. The MLP neural network has been used to predict the physical properties of XLPE insulating material submitted to UV radiations. As long as the predicted values are close to experimental ones, a good accordance has been obtained which proves the best performance of the used neural network. In the case of the contact angle, the maximal relative error reaches 9.47%, against 8.15%for the weight loss and 3.45% for the work of water adhesion. The best accuracy is obtained for the water absorption with relative error not exceeding 2.60%. The different maximal errors of the studied electrical, mechanical, and physical characteristics are recapitulated in Table 2.

4.4. Prediction of XLPE properties for longer periods

Taking into consideration the results of our investigation, it is recommended to use the developed neural network to predict several characteristics evolutions for very important exposure times. To achieve this goal, the proposed

ANN network has been trained for full experimental interval (240 h). The prediction phase is accomplished until reaching 1000 h. Three properties namely volume resistivity, tensile strength, and weight loss have been selected and presented in Figure 5. Along 1000 h, the obtained results show that the volume resistivity decreases by 15% against 26% for the tensile strength, at the moment where the weight loss stabilizes around 0.023%.

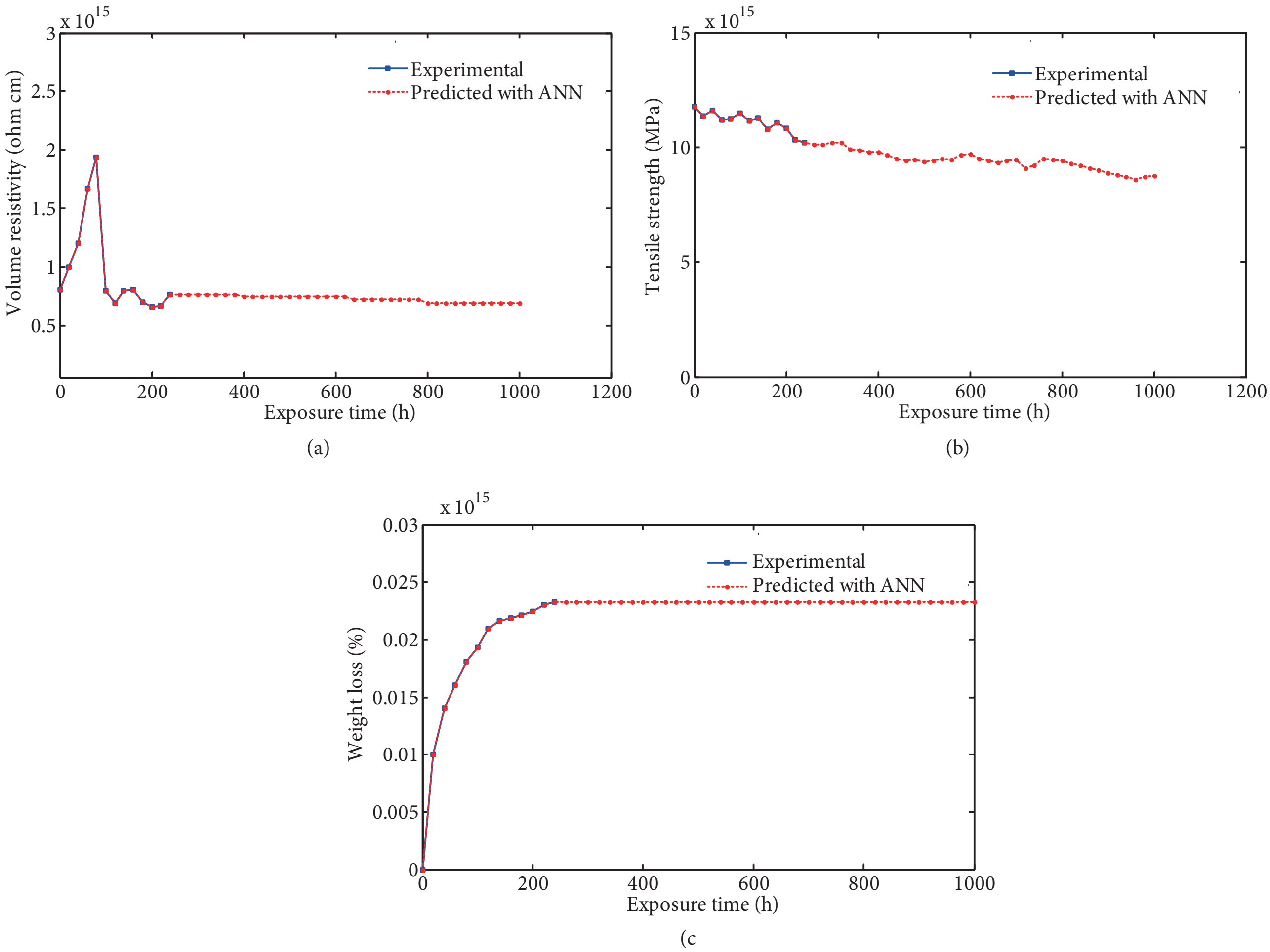

Figure 5. Experimental and predicted as function of UV exposure time of: (a) DC volume resistivity, (b) tensile strength, and (c) weight loss.

5. Conclusion

This paper deals within experimental and predicted XLPE insulating material properties under UV-aging. The experimental results show that the XLPE properties are sensitive to UV radiations. Indeed, a decline in mechanical properties and hydrophobicity, and an increase in the water retention amount have been noticed. Moreover, the surface resistivity decreases rapidly during the first 100 h of aging and then stabilizes. On the other hand, the volume resistivity decreases slightly with aging time.

An ANN network has been designed to predict and extrapolate XLPE properties. This proposed prediction model demonstrates promising potential in the area of XLPE insulating material characterization since it shows a good agreement with the obtained experimental results. Predicted and laboratory results are compared to validate the proposed neural network. The proposed ANN practically reproduces the same nonlinear characteristics obtained in laboratory with acceptable errors. The maximum relative error values of electrical, mechanical, and physical properties are 8.55% , 10.93%, and 9.47%, respectively. The proposed ANN proves a great effectiveness and can be extended to predict any other characteristics. The prediction extension for longer periods may give important information related to the life time of the high-voltage power cable insulation.

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References

[1] Frutos F, Acedo M, Mudarra M, Belana J, Ã rrit J et al. Effect of annealing on conductivity in XLPE mid-voltage cable insulation. Journal of Electrostatics 2007; 65 (2): 122-131. doi: 10.1016/j.elstat.2006.07.015

[2] Ying L, Xiaolong C. A novel method for the insulation thickness design of HV XLPE cable based on electrical treeing tests. IEEE Transactions on Dielectrics and Electrical Insulation 2014; 21 (4): 1540-1546. doi: 10.1109/TDEI.2014X.004250

[3] NÃ³brega AM, Martinez MLB, de Queiroz AAA. Analysis of the XLPE insulation of distribution covered conductors in Brazil. Journal of Material Engineering Performance 2014; 23 (3): 723-735.

[4] Fothergill J, Dodd S, Dissado L, Liu T, Nilsson U. The measurement of very low conductivity and dielectric loss in XLPE cables: a possible method to detect degradation due to thermal aging. IEEE Transactions on Dielectrics and Electrical Insulation 2011; 18 (5): 1544-1553.doi: 10.1109/TDEI.2011.6032823

[5] Gulmine JV, Akcelrud L. Correlations between structure and accelerated artificial ageing of XLPE. European Polymer Journal 2006; 42(3): 553-562. doi: 10.1016/j.eurpolymj.2005.09.006

[6] Bouanga C, Couderc H, Frechette M, Savoie S, Malucelli G et al. Dielectric study of low glass transition temperature cycloaliphatic UV-curable epoxy networks. EEE Transactions on Dielectrics and Electrical Insulation 2012; 19 (4): 1269-1282. doi: 10.1109/TDEI.2012.6260001

[7] Santhosh TV, Gopika V, Ghosh AK, Fernandes BG. An approach for reliability prediction of instrumentation & control cables by artificial neural networks and Weibull theory for probabilistic safety assessment of NPPs. Reliability Engineering & System Safety 2018; 170: 31-44. doi: 10.1016/j.ress.2017.10.010

[8] Fang S, Du B, Zhu X, Han T. Effect of temperature gradient on electrical tree in XLPE from 0 to 196$^{\circ}C$. IEEE Transactions on Applied Superconductivity 2019; 29 (2): 1-4. doi: 10.1109/TASC.2018.2890468

[9] Zhou K, Huang M, Tao W, He M, Yang M. A possible water tree initiation mechanism for service-aged XLPE cables: Conversion of electrical tree to water tree. IEEE Transactions on Dielectrics and Electrical Insulation 2016; 23(3): 1854-1861. doi: 10.1109/TDEI.2016.005405

[10] Liu Y, Cao X. Electrical tree growth characteristics in XLPE cable insulation under DC voltage conditions. IEEE Transactions on Dielectrics and Electrical Insulation 2015; 22(6): 3676-3684. doi: 10.1109/TDEI.2015.005222

[11] Gu X, He S, Xu Y, Yan Y, Hou S et al. Partial discharge detection on 320 kV VSC-HVDC XLPE cable with artificial defects under DC voltage. IEEE Transactions on Dielectrics and Electrical Insulation 2018; 25(3): 939-946. doi: 10.1109/TDEI.2018.006940

[12] Ouyang B, Li H, Zhang X, Wang S, Li J. The role of micro-structure changes on space charge distribution of XLPE during thermo-oxidative ageing. IEEE Transactions on Dielectrics and Electrical Insulation 2017; 24(6): 3849-3859. doi: 10.1109/TDEI.2017.006523

[13] Douminge L, Mallarino S, Cohendoz S, Feaugas X, Bernard J. Extrinsic fluorescence as a sensitive method for studying photo-degradation of high density polyethylene part I. Current Applied Physics 2010; 10 (4): 1211-1215. doi: 10.1016/j.cap.2010.02.045

[14] Suljovrujic E. Post-irradiation effects in polyethylenes irradiated under various atmospheres. Radiation Physics and Chemistry 2013; 89: 43-50. doi: 10.1016/j.radphyschem.2013.04.003

[15] Shimada A, Sugimoto M, Kudoh H, Tamura K, Seguchi T. Degradation distribution in insulation materials of cables by accelerated thermal and radiation ageing. IEEE Transactions on Dielectrics and Electrical Insulation 2013; 20(6): 2107-2116. doi: 10.1109/TDEI.2013.6678859

[16] Aljoumaa K, Ajji Z. Mechanical and electrical properties of gamma-irradiated silane crosslinked polyethylene (Si-XLPE). Journal of Radioanalytical and Nuclear Chemistry 2016; 307 (2): 1391-1399.

[17] Sugimoto M, Shimada A, Kudoh H, Tamura K, Seguchi T. Product analysis for polyethylene degradation by radiation and thermal ageing. Radiation Physics and Chemistry 2013; 82: 69-73. doi: 10.1016/j.radphyschem.2012.08.009

[18] Bessissa L, Boukezzi L, Mahi D. Influence of fuzzy parameters on the modeling quality of xlpe insulation properties under thermal aging. Fuzzy Information and Engineering 2016; 8(1): 101-112. doi: 10.1016/j.fiae.2016.03.006

[19] Doblies A, Boll B, Fiedler B. Prediction of thermal exposure and mechanical behavior of epoxy resin using artificial neural networks and fourier transform infrared spectroscopy. Polymers (Basel) 2019; 11(2). doi: 10.3390/polym11020363

[20] Gopinath S, Sathiyasekar K, Padmanaban S, Chokkalingam B. Insulation condition assessment of high-voltage rotating machines using hybrid techniques. IET Generation, Transmission & Distribution 2019; 13(2): 171-180. doi: 10.1049/iet-gtd.2018.6500

[21] Chen K, Huang C, He J. Fault detection, classification and location for transmission lines and distribution systems: a review on the methods. High Voltage 2016; 1 (1): 25-33. doi: 10.1049/hve.2016.0005

[22] Roy NK, Potter WD, Landau DP. Polymer property prediction and optimization using neural networks. IEEE Transactions on Neural Network 2006; 17(4): 1001-1014. doi: 10.1109/TNN.2006.875981

[23] Boukezzi L, Boubakeur A. Use of neural network algorithms in prediction of XLPE HV insulation properties under thermal aging. In: Zamojski W, Mazurkiewicz J, Sugier J, Walkowiak T, Kacprzyk J (editors). New Results in Dependability and Computer Systems. Heidelberg: Springer, 2013, pp. 53-61.

[24] Khan MYA, Koo J-Y. Neural network based diagnosis of partial discharge defects patterns at XLPE cable under DC stress. Electrical Engineering 2017; 99(1): 119-132.

[25] Akbal B. Applications of artificial intelligence and hybrid neural network methods with new bonding method to prevent electroshock risk and insulation faults in high-voltage underground cable lines. Neural Computing and Applications 2018; 29(8): 97-105.

[26] Mohanty S, Ghosh S. Artificial neural networks modelling of breakdown voltage of solid insulating materials in the presence of void. IET Science, Measurement & Technology 2010; 4(5): 278-288. doi: 10.1049/iet-smt.2010.0005

[27] Boukezzi L, Bessissa L, Boubakeur A, Mahi D. Neural networks and fuzzy logic approaches to predict mechanical properties of XLPE insulation cables under thermal aging. Neural Computing and Applications 2017; 28(11): 3557-3570.

[28] Hedir A, Moudoud M. Effect of ultraviolet radiations on medium and high voltage cables insulation properties. International Journal of Engineering and Technology 2016; 8(5): 2308-2317. doi: 10.21817/ijet/2016/v8i5/160805406

[29] Hedir A, Jbara O, Moudoud M, Slimani F, Rondot S et al. Behaviour of cross-linked polyethylene used as high voltage power cables insulation due to environmental constraints. In :2018 International Conference on Electrical Sciences and Technologies (CISTEM); Maghreb, Algeria; 2018. pp. 1-4. doi: 10.1109/CISTEM.2018.8613596

[30] Andrzejuk W, Barnat-Hunek D, Fic S, StyczeÅ J. Wettability and surface free energy of mineral-asphalt mixtures with dolomite and recycled aggregate. IOP Conference Series: Materials Science and Engineering 2019; 471(3): 032011. doi: 10.1088/1757-899X/471/3/032011

[31] Malik ZA, Haleem N, Malik MH, Tanwari A. Predicting the tensile strength of polyester/cotton blended woven fabrics using feed forward back propagation artificial neural networks. Fibers and Polymers 2012; 13(8): 1094-1100.

[32] Beale M, Demuth H. Neural network toolbox. Neural Netw. Toolbox, Userâ s Guide, 2004.

[33] Bok-Hee Y, Chang-Su H. Surface degradation of HTV silicone rubber and EPDM used for outdoor insulators under accelerated ultraviolet weathering condition. IEEE Transactions on Dielectrics and Electrical Insulation 2005; 12 (5): 1015-1024. doi: 10.1109/TDEI.2005.1522194

[34] Hedir A, Moudoud M, Rondot S, Jbara O, Slimani F. UV-Aging Effect on the Behaviour of Cross-linked Polyethylene Used as High Voltage Power Cables Insulation. In : SociÃ©tÃ© FranÃ§aise d'Ã©lectrostatique; France; 2018. pp. 7-11.

[35] Kaczmarek H, O dak D, Malanowski P, Chaberska H. Effect of short wavelength UV-irradiation on ageing of polypropylene/cellulose compositions. Polymer Degradation and Stability 2005; 88(2): 189-198.doi: 10.1016/j.polymdegradstab.2004.04.017

[36] Eve S, Mohr J. Effects of UV-irradiation on the thermo-mechanical properties of optical grade poly(methyl methacrylate). Applied Surface Science 2010; 256(9): 2927-2933. doi: 10.1016/j.apsusc.2009.11.052

[37] Jofre-Reche JA , MartÃn-MartÃnez JM. Selective surface modification of ethylene-vinyl acetate and ethylene polymer blend by UVâ ozone treatment. International Journal of Adhesion and Adhesives 2013; 43: 42-53. doi: 10.1016/j.ijadhadh.2013.01.010

[38] Oâ Connell C, Sherlock R, Ball MD, AszalÃ³s-Kiss B, Prendergast U et al. Investigation of the hydrophobic recovery of various polymeric biomaterials after 172 nm UV treatment using contact angle, surface free energy and XPS measurements. Applied Surface Science 2009; 255(8): 4405-4413. doi: 10.1016/j.apsusc.2008.11.034

[39] Rosu D, Rosu L, Mustata F, Varganici C-D. Effect of UV radiation on some semi-interpenetrating polymer networks based on polyurethane and epoxy resin. Polymer Degradation and Stability 2012; 97(8): 1261-1269. doi: 10.1016/j.polymdegradstab.2012.05.035

[40] Liu H, Cash G, Birtwhistle D, George G. Characterization of a severely degraded silicone elastomer HV insulator - an aid to development of lifetime assessment techniques. IEEE Transactions on Dielectrics and Electrical Insulation 2005; 12(3): 478-486. doi: 10.1109/TDEI.2005.1453452