Turkish Journal of Electrical Engineering and Computer Sciences

Volume 29 | Number 5 Article 12

1-1-2021

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Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2021) 29: 2437 – 2449
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doi:10.3906/elk-2105-27

Prediction of long-term physical properties of low density polyethylene (LDPE) cable insulation materials by artificial neural network modeling approach under environmental constraints

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Received: 04.05.2021 • **Accepted/Published Online:** 24.06.2021 • **Final Version:** 23.09.2021

Abstract: This study quantifies long-term physical properties of low density polyethylene (LDPE) cables insulations exposed to environmental constraints such as UV radiation and temperature via both experimental measurements and mathematical modeling approach. For this purpose, tensile test and electrical breakdown test were carried out to determine elongation at break, tensile strength, and dielectric strength of unaged and aged specimens, respectively. Experimental results showed that both UV and temperature exposures affected the LDPE properties, significantly. A supervised artificial neural network (ANN) trained by the Levenberg–Marquardt algorithm was designed for predicting the long-term characteristics of specimens and also for minimizing the experimental procedures. Modeling work showed that the proposed ANN yielded successful estimations and predictions about the service life of thermoplastic cable insulation materials for maintaining the process.

Key words: Low density polyethylene (LDPE),UV radiations, temperature, artificial neural network (ANN)

1. Introduction

During the last few decades, semi-crystalline polymers used in outdoor applications, such us electrical insulation, have become the focus of several attractive investigations [1, 2]. The widespread use of these materials is due to their excellent properties and low cost [3]. Polyethylene is one of the most largely used semi-crystalline polymers in cable insulation and cable accessories because of its outstanding application performances, such as very high flexibility and toughness at low temperatures, low moisture absorption, superior resistance for solvents, acids, and alkaline compounds, and ease of recycling and processing [4]. Polyethylene, the most extensively employed member of polyolefins in daily life and industrial applications, possesses several types and commercial grades. The basic classification is based on the chain structure, mainly degree of branching, and density values, namely low density polyethylene (LDPE), linear low density polyethylene (LLDPE), medium density polyethylene (MDPE), and high density polyethylene (HDPE).

LDPE is used in a wide variety of fields such as packaging bags and containers, shrink-wraps and stretch films, horticultural and agricultural films, sheathings, pipes, fittings, machine parts, etc. [5, 6]. LDPE is also

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commonly used in power cable insulation applications due its outstanding dielectric and mechanical properties, high molecular weight and hydrophobic nature [7]. Polyethylene is a much green alternative for the conventional poly (vinyl chloride) (PVC)-based cable insulation materials because its non-polar and halogen-free chemical structure. Nevertheless, LDPE undergoes serious and irreversible structural damages when it is subjected to the different operating and environmental conditions. These structural changes lead to considerable reduction in physical properties and application performances of LDPE insulating materials.

Many investigations have been devoted to monitoring structural and physical behaviors of LDPE insulation operating under aggressive environmental stresses such as heat and atmospheric radiations. Hiejima et al. [8] investigated the microscopic structural changes during photo degradation of LDPE. Yagoubi et al. [9] examined the unavoidable oxidation of molecular structure of LDPE under environmental exposure. Luyt et al. [10] studied the effectiveness of different LDPE formulations in reducing the UV/heat degradation extent. Benda et al.[11] examined the polarization of electron-beam irradiated LDPE films.

It is well known that the effective life-time of cables insulation is governed by its resistance to environmental constraints [12]. It has been concluded in several investigations that heat is considered as one of the most destructive effects among different environmental factors for leading the degradation of cable insulation [13] – [15]. Suraci et al. [16] investigated the thermal degradation phenomena on LDPE through electrical and chemical measurements. Wang et al. [17] studied the effect of thermal aging on the electrical properties and space charge behavior of LDPE. Li et al. [18] showed that thermo-oxidative atmosphere during thermal aging significantly affects the electrical performances of LDPE.

Radiations are also considered as one of the most dangerous deteriorating factors for polymers, specifically for cable insulation materials [19]. It has been reported that radiation induces several degradation mechanisms, namely, chain scissions and/or cross linking, which lead to an alteration of dielectric and mechanical properties of insulating materials. Suresh et al. [20] investigated the modification of LDPE mechanical and surface properties during UV-exposure. Lanfranconi et al. [21] put into evidence that LDPE activation energy increases under gamma irradiation effect, which limits the crystallization process. Martinez et al. [22] showed that under UV radiations, LDPE underwent photo-oxidation leading to chain scissions, formation of carbonyl and vinyl groups, and hydrophilic surface modification.

It should be noted that damaging effects of both heat and radiation on the structural and physical properties of polymers are very slow processes, and expressive results are generally brought out over a very long period of time. The environmental aging and testing work are difficult, expensive, and time-consuming procedures. Moreover, test results should also be statistically reliable. In recent years, extensive research efforts have been spent for reducing the cost and consumed time of experimental studies [23]. Therefore, developing reliable mathematical models and predicting long-term physical properties of a specimen are regarded as crucial attempts in material science. Like in many fields [24, 25], artificial intelligence approaches are also commonly used to predict the response of insulating materials when they are subjected to different stresses [26]. The artificial neural network (ANN) is one of the most frequently used approaches among these models. The most powerful aspect of ANNs is the multilayer perceptron (MLP) network trained by back-propagation algorithm. A perceptron can be considered as an artificial neuron, where the direct propagation is often used in the control application of nonlinear systems [27]. In a perceptron, the neurons are arranged in layers; there are no connections between the neurons of the same layer and the connections are only made with the neurons of the lower layer. Over the last two decades, various kinds of ANNs are used to predict and diagnose high voltage insulation materials because of the various abilities of ANNs [28, 29]. Bessissa et al. [30] investigated the prediction of properties of high voltage cable insulation material under thermal effects using ANN approach. Poluyanovich et al. [31] used multistage ANN for estimating resource of cable lines insulating materials. Jabha et al. [32] studied the failure prediction in crosslinked polyethylene (XLPE) power cables using ANN approach.

The aim of this study was to analyze the effects UV radiation and thermal constraint on the physical properties of LDPE power cables insulation by ANN. In addition, MLP network approach was employed to predict long-term dielectric and mechanical properties of specimens under these environmental stresses. To the best of our knowledge, a study has not been reported yet in this area. We previously experimented the effects of UV and thermal aging on the mechanical properties of LDPE and presented [33, 34]. Technical concept of the work could be divided into two sections: (i) an experimental study and (ii) a prediction by using artificial intelligence tool. The experimental part consists two aging processes and testing studies. A group of LDPE specimens were exposed to heat in an oven at 90 °C for 5000 h. Another group of specimens were irradiated by UV using low-pressure vapor fluorescent lamps for 480 h. It should be noted that the intensity of UV emitted by the lamps is 10.5 times higher than the natural UV, which corresponds to exposure of 5040 h. The dielectric and mechanical properties of exposed specimens such as dielectric strength, elongation at break and tensile strength were measured. In the second part, LDPE characteristics were predicted by introducing a supervised ANN. A MLP network trained by back-propagation algorithm, called Levenberg–Marquardt, was established to accomplish this task. The supervised ANN is introduced to predict some LDPE properties exceeding largely the experimental ones. In such technique, the experimentally obtained database was used to train and evaluate the neural network performances. The predicted values were then compared to the experimental results to assess the reliability of MLP for evaluating LDPE properties.

2. Material and methods

2.1. Material

LDPE test specimens were square plates having the size of $130 \times 130mm$ and the thickness of $2 \pm 0.2mm$ prepared by using a commercial-grade of LDPE (Alcudia CP-104, Repsol Company) with a melt flow index (MFI) of 2.4 g/10min (ASTM D1238) and density of 0.920 g/cm^3. Depending on the nature of tests, samples in different forms are cut from the obtained results. For dielectric strength test, square samples of $60 \times 60mm$ were used. Mechanical tests were performed using samples in dumbbell-shaped form of 50 mm length.

2.2. UV aging

The UV aging of LDPE samples was performed in an accelerated UV-aging chamber. The irradiation was accomplished using eight low-pressure vapor fluorescent lamps of 36 W. The irradiation wavelength was in the range of 350–400 nm. The distance between samples and lamps was $10cm$. The total aging time was 480 h. The properties of specimens, namely, elongation at break, tensile strength and dielectric strength were measured at 48 h exposure intervals. The UV exposure was applied at $55 \pm 5C$ without controlling humidity.

2.3. Thermal aging

A thermo-ventilated oven fixed at a constant temperature of $90 \pm 2C$ was used for thermal aging experiments. All the samples were vertically suspended and subjected to the thermal constraint during 5000 h inside the oven. It should be declared that the aging temperature did not yield a physical deformation for the samples.

2.4. Mechanical tests

Tensile tests were performed in a universal tensile test machine with a crosshead speed of $50mm/min$.Tensile strength and elongation at break values of specimens were quantified as a function of aging time, as well as the general relaxation behavior of material under mechanical load using a Schnek–Trebel testing machine according to the IEC 60811.1.1 (International Electrotechnical Commission) standard.

2.5. Electrical breakdown test

An AC breakdown test system which can supply a continuously adjustable power frequency AC voltage from 0 to $100kV$ was implemented and used. The flat electrodes with a diameter of $6mm$ and the $60 \times 60mm$ LDPE square test tube were both immersed in a transformer oil medium to prevent bypass. The breakdown tests were carried out at room temperature under a linearly increasing voltage of $2kV/s$. For each aging period, six different specimens were tested.

2.6. Prediction network for LDPE sample properties

In the prediction part of the study, a three-layer network with a sigmoid transfer function was generated under Matlab/Simulink setting to predict LDPE sample properties. Architecture of the ANN is shown in Figure 1. As seen in the network scheme, aging time is the input in this ANN and the estimated and calculated outputs are compared. Therefore, the obtained estimated progression error is also used as a second input to update the weights.

The Levenberg–Marquardt back-propagation (LMBP) algorithm was used to run the generated MLP. The LMBP is considered as one of the most efficient algorithms used for running the feed-forward neural network (FFNN) [35]. While back-propagation is a steepest descent algorithm, the Levenberg–Marquardt algorithm is derived from the Newton's method that is used specifically for minimizing sum-of-square error of nonlinear functions during ANN running. Back propagation is monitored by the Widrow–Hoff learning rule [36], and the Matlab/Simulink tool is utilized for designing the developed ANN.

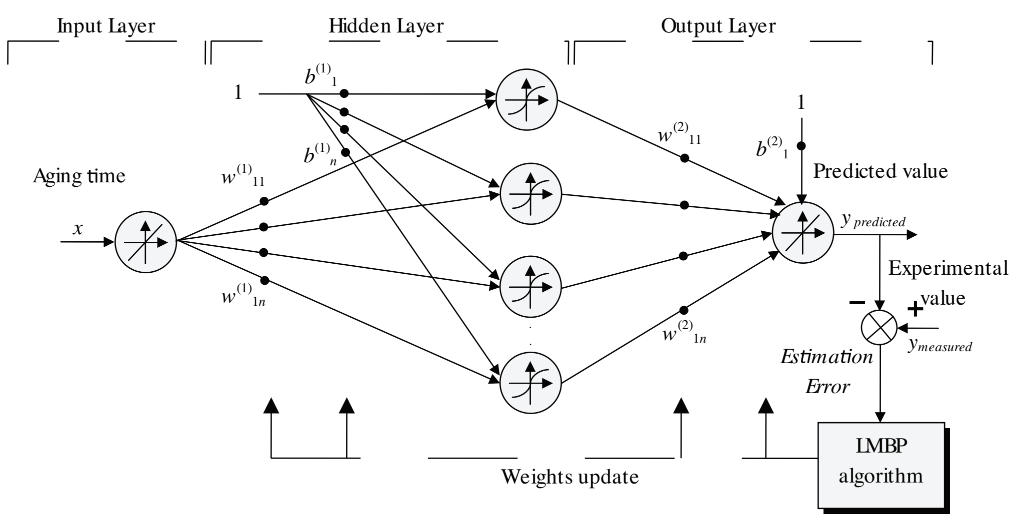

Figure 1. The built MLP model for predicting LDPE insulation properties.

The running function is used as a network training function that updates weight and bias values following the Levenberg–Marquardt (LM) optimization.

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

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

where a, c, and γ are the parameters allowing to extract asymmetric or symmetric functions with various profiles [37]. $\nu_j(n)$ is the neuron activity.

The weight matrix is updated during the running session according to the following equation:

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n+1) \tag{2}$$

where the parameter $\Delta w_{ij}(n+1)$ is the variation of weight matrix given by the general expression:

$$\Delta w_{ij}(n+1) = \eta \delta_j(n) x_i(n) \tag{3}$$

where:
η: The learning rate; its value is positive and less than 1;
δ_j: The neuron j input error;
x_i: The neuron i input.

The activation functions and the parameter values utilized in the presented ANN network are defined in Table 1. The ANN parameters are selected on the basis of trial and error. The ANN depicted in Figure 1 possesses the following architecture: One linear neuron in both input and output layers, and variable tan-sigmoid neurons in the hidden layer.

For choosing the best network architecture, the hidden layer's number of neurons went from 10 to 100. The number of neurons in the hidden layer is changed manually. It should be mentioned that the finest prediction results are found in this range.

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

	Input layer	Hidden layer	Output layer
Activation function	linear	symmetric sigmoid	linear
Parameter- γ	-	2.0	-
Parameter- a	-	2.0	-
Parameter- c	-	–1.0	-
Number of neurons	1	10–100	1
Learning coefficient η		0.05	
Number of inputs		1	
Number of outputs		1	
Final error		$\prec$5.10-6	

3. Results and discussion

The experimental and predicted results describing the different properties of LDPE are shown in Figures 2-5, as a function of aging time. In the case of UV-aging, the network was runned using about 40% of each characteristic's data; the learning time was $192h$, and the remaining data (60%), which represents extra $288h$ was used to test the neural network. In the case of thermal aging, about 40% of data were used to run the network; the learning time was $2000h$, and the 60% of remaining data corresponding to $3000h$ were used to test the neural network.

3.1. UV-aging

Figures 2(a) and 2(b) illustrate the comparison of experimental and predicted values of elongation at break and tensile strength of specimens as a function of UV-exposure time, respectively. Tensile test results indicated that both elongation at break and tensile strength showed non-monotonic variation. The elongation at break value of unaged sample was found to be 522%. This value increased to 630% after $48h$ of UV exposure. This increase in ultimate elongation by the UV exposure might be explained with the improving physical and intermolecular interactions between PE chains due to increase in polarity (generally characterized by carbonyl index,CI) of polymer occurring generally during the first UV-exposure phase, as reported by Skeikh et al.[38]. At the end of exposure, elongation at break value then decreased slightly and reached to 550%. It was found that the tensile strength decreased from $11.23MPa$ to $9.46MPa$ with a $48h$ of UV-exposure. This parameter showed fluctuations between $48 - 288h$ and reached to $10.66MPa$ at the end of exposure. This behavior might be originated from a competition between chains scission and crosslinking.

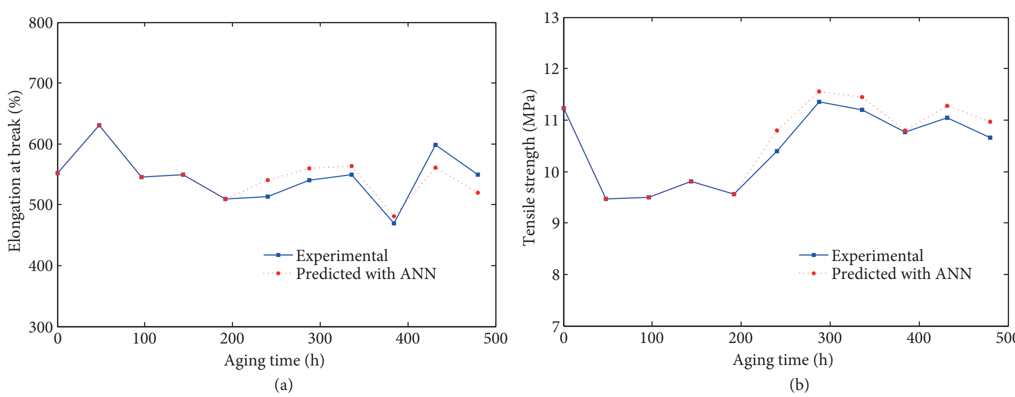

Figure 2. Experimental and predicted mechanical properties according to UV-aging time, (a) elongation at break, (b) tensile strength.

Learning time and prediction time were chosen as 192 and $288h$, respectively for predicting the mechanical properties of LDPE. The results showed that the MLP yielded a successful prediction neural network with reasonable errors. As presented in Table 2, the relative maximum errors went up from 2.28% to 5.76% and from 1.64% to 3.70% for the elongation at break and tensile strength, respectively.

Figure 3 compares the experimental and predicted dielectric strength values as a function of aging time. It is clearly seen that LDPE shows a relatively high initial dielectric strength of $33.4kV/mm$ and then this value decreases rapidly to $26.4kV/mm$ as a result of $144h$ of UV-exposure. Dielectric strength exhibited a slight increase between $144 - -384h$, then reduced to a minimum value, $24.1kV/mm$, at the end of UV-exposure.

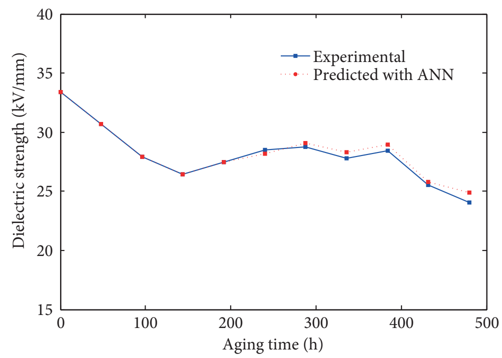

Figure 3. Experimental and predicted values of dielectric strength according to UV-aging time.

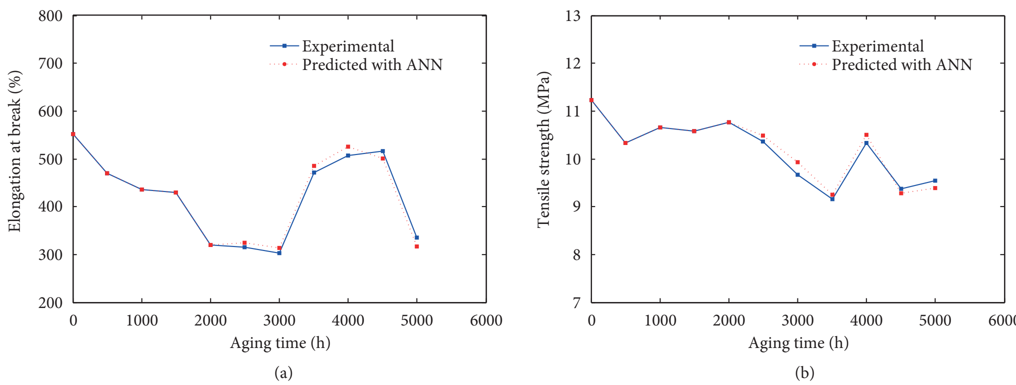

Figure 4. Experimental and predicted mechanical properties according to thermal aging time, (a) elongation at break, (b) tensile strength.

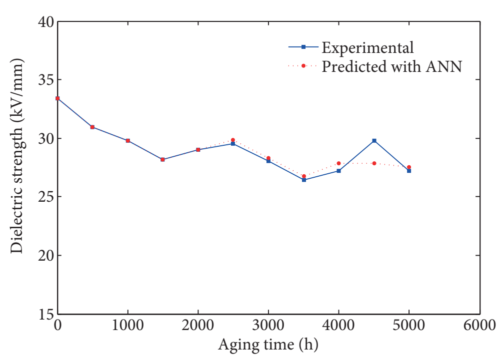

Figure 5. Experimental and predicted values of dielectric strength according to thermal aging time.

From the beginning to the end of aging test, a significant decrease in dielectric strength was recorded as 28%. This may be the result of the presence of different oxidative products such as polar carbonyl and hydroxyl groups, originated from photo-oxidation reactions under the UV radiation aging [39]

The back-propagation neural network was also applied to predict the dielectric strength of LDPE. As shown in Figure 4, it is noticeable that the predicted values are very close to the experimental data. Thus, it can be concluded that the MLP predictions are highly consistent with the experimental data. Indeed, the relative maximum error for the dielectric strength did not exceed 3.25%, which confirms the prediction quality.

Table 2. Relative maximum errors of properties prediction under UV-aging in %.

Aging time (h)	Elongation at break	Tensile strength	Dielectric strength
240	5.00	3.70	0.99
288	3.57	1.64	1.09
336	2.30	2.09	1.90
384	2.28	3.00	1.76
432	6.59	2.04	0.93
480	5.76	2.73	3.25

3.2. Thermal aging

Figures 4 (a) and 4(b) show the variation of experimental and predicted elongation at break and tensile strength as a function of thermal aging time, respectively.

It was obtained that both parameters exhibited an irregular variation. Tensile strength slightly decreased from $11.23MPa$ to $9.55MPa$ with the thermal aging of $5000h$. A similar behavior was also observed for the elongation at break: decrease from the 552.5% (unaged specimen) to 315% at the end of exposure. These decreases in the mechanical characteristics could be related to thermo-oxidative degradation of polyethylene chains accompanied by chains scission reactions [40]. Chains scission could reduce the molecular weight, which leads to a serious weakness of the material. Shi et al. [41] reported that the loss of mechanical performance of HDPE depending on various thermal effects was caused by thermal oxidation events which induced to reduction in molecular weight and chains mobility, and the increase in crystallinity.

The prediction results show that the MLP is an efficient prediction neural network with reasonable errors. As seen in Table 3, the relative maximum error goes up from 2.88% to 5.67% for elongation at break and does from 1.07% to 2.61% for tensile strength.

Table 3. Relative maximum errors of properties prediction under thermal aging in %.

Aging time (h)	Elongation at break	Tensile strength	Dielectric strength
2500	3.07	1.14	1.17
3000	3.09	2.61	1.02
3500	2.88	1.08	1.34
4000	23.68	1.71	0.32
4500	2.99	1.07	6.85
5000	5.67	1.70	1.12

Figure 5 compares the experimental and predicted dielectric strength (DS) values as a function of thermal exposure time. It was experimentally observed that the DS was significantly affected from thermal constraint. The DS of unaged specimen was found to be $31.61kV/mm$ then dropped to $28.20kV/mm$ after a $1500h$ of thermal aging. The DS value showed some fluctuations for longer aging periods than $1500h$ and reached to $27.19kV/mm$ at the end of thermal treatment. It can be noticed that the DS reduced by 14% of its initial value by the applied thermal procedure. This property loss may be attributed to the thermo-oxidative degradation, which is followed by ionization of the material and formation of charge carrier inside the material [34]. Kim et al.

[42] reported that application of high temperature thermal aging or annealing for long time could facilitate the creation of short chains due to random chain scissions, micro-cracks, voids and other structural defects which leads to the decrease of dielectric strength of XLPE materials. Our results are consistent with the previously reported ones and the suggested mechanism.

In order to predict the DS of LDPE, the back-propagation neural network was also applied. As shown in Figure 5, the predicted values are close to the experimental ones. Therefore, it can be concluded that the MLP predictions are in good agreement with the experimental data. Indeed, the relative maximum error for the dielectric strength did not exceed 6.85.

3.3. Prediction of long-term properties of LDPE

The prediction of long-term properties allow us to understand the physical behavior and application performance of LDPE for insulation life-time under two fundamental environmental constraints. Indeed, the evolution of dielectric strength, tensile strength, and elongation at break predictions can be considered as the aging evaluation parameters. The proposed ANN can be successfully used to predict the different properties under UV and thermal aging. The prediction phase is accomplished until $1440h$ for UV aging and $15000h$ for thermal aging. As given in Figure 6, the obtained results along $1440h$ show that elongation at break, tensile strength and dielectric strength of LDPE decreases by 26.51%, 15.22%, and 48.87%, respectively as a function of UV exposure time. Figure 7 represents the prediction curves of parameters as a function of thermal aging time. It is seen in this figure that the parameters decreases by 55.11%, 22.97%, and 44.26%, respectively after 15000 h aging. The time where the DS value drops to 50% of the initial value could be considered as an indicative point for the degradation issues for two aging mechanisms evaluated in this study. Based on the results, it can be concluded that the LDPE insulated cables could be changed after exposing $1440h$ of an intensive UV radiation and $15000h$ of thermal stress.

4. Conclusion

This study reported analytical test results and proposed an ANN approach for quantifying and predicting the effects of environmental constraints such as UV radiations and thermal exposure on the physical properties of LDPE insulating materials. The experimental results showed that photo-oxidation and thermo-oxidation phenomena led to loss of physical performances of polyolefin insulation materials possibly due to formation of structural defects associated with the chemical degradation. It is a well-known fact that chemical degradation of polyolefins at low temperatures is a quite slow process. Moreover, detection and quantification of degradating species is very difficult even in the case of employing modern analytical techniques. The further life-time estimation is a much more complex phenomenon because it depends on too many parameters. The degradation induces chain scission and yields oxidative products. Therefore, “property modeling” attempts have been considered as alternative, fast and versatile solutions in materials science, particularly in polymer science, in recent years. The prediction approach used in this study provided a promising potential for the characterization studies of long-term application performances of LDPE insulating materials. The modeling results indicated that the developed ANN showed a high prediction quality since the experimental results were in good agreement with the predicted ones. Consequently, it has been concluded that the prediction by the ANN extrapolation method is a very practical way to reduce testing time and estimate the service time of cable insulation materials.

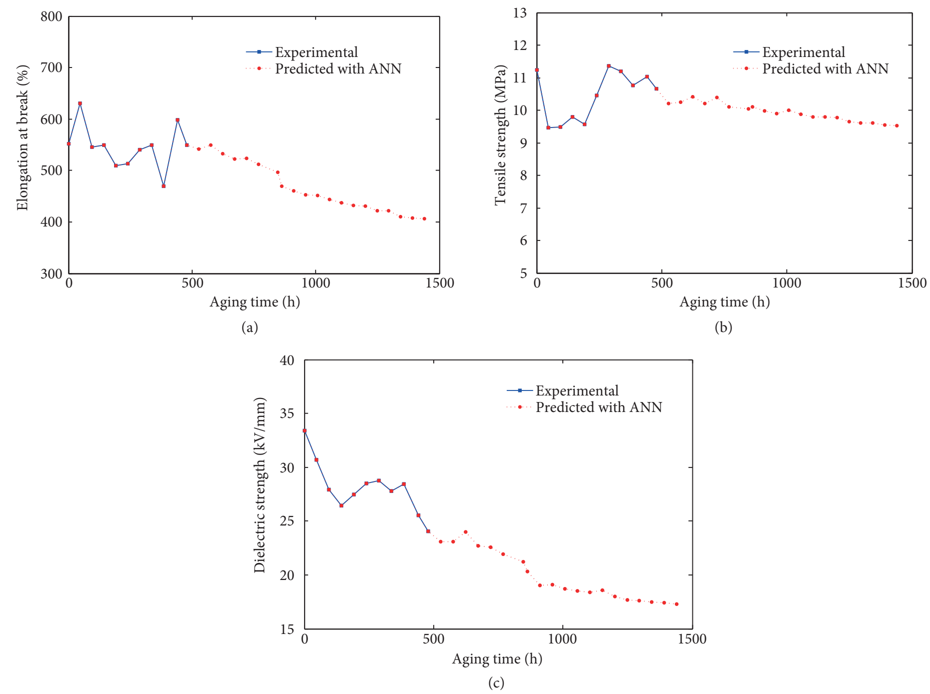

Figure 6. Experimental and predicted elongation at break, tensile strength and dielectric strength as function UV-exposure time.

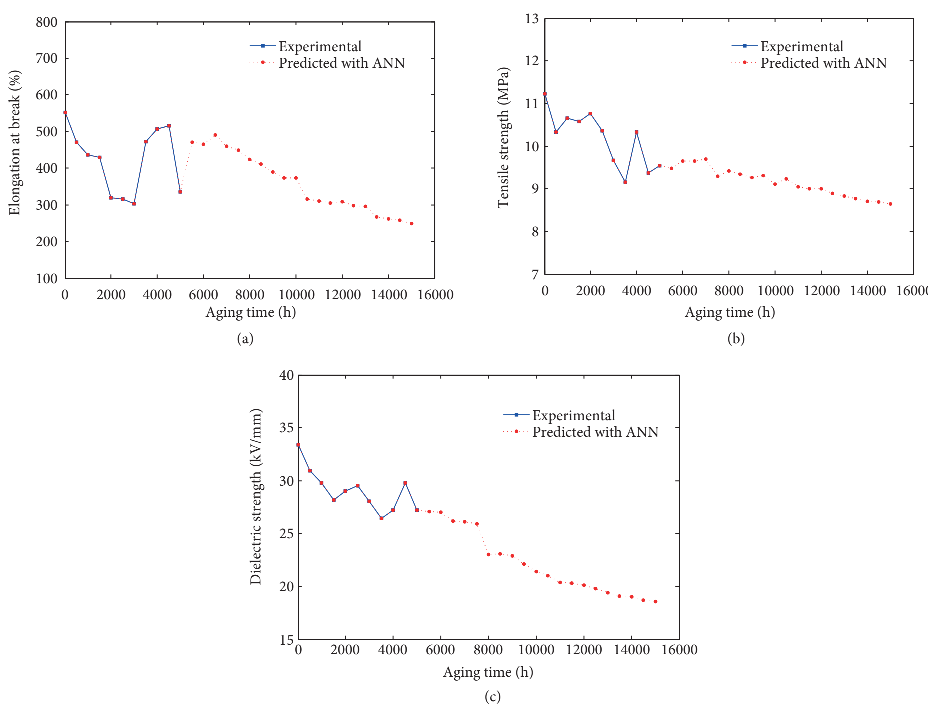

Figure 7. Experimental and predicted elongation at break, tensile strength and dielectric strength as function of thermal aging.

Acknowledgment

The authors thank the Algerian Ministry of Higher Education and Scientific Research for supporting this work through the project PRFU A01L07UN150120180005.

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