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EVALUATION OF THE DIELECTRIC STRENGTH BEHAVIOR OF RUBBER BLENDS USING FEED-FORWARD NEURAL NETWORK IN DIFFERENT ENVIRONMENTAL CONDITIONS

Mansour M. M. Abdalla[1]*, Loai S. Nasrat [2], A. H. I. Mansour [2], El-said A. Othman [3]

[1] Electrical Power & Machines Dept., Faculty of Engineering, Al-Azhar University, Qena, Egypt.

[2] Electrical Power &Machines Dept., Faculty of Engineering, Aswan University, Aswan, Egypt.

[3] Electrical Power &Machines Dept., Faculty of Engineering, Al-Azhar University, Cairo, Egypt.

*Corresponding author's E-mail: Mansourabdalla.2038@azhar.edu.eg

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ABSTRACT

Polymers have been frequently employed in electrical applications because of their strong thermal and electrical insulating qualities, low density, and chemical resistance. In this study, a comparison between the behaviour and electrical properties of polymer blends and the results of artificial neural network (ANN) modelling has been conducted. Five samples of silicon rubber (SiR) and ethylene propylene diene monomer (EPDM) were prepared in different proportions. A dielectric test was used to test the dielectric performance of insulation samples under various polluting conditions such as dry, wet, low salinity, and high salinity wet according to ASTM standards. Percentage of blend and dielectric strength were used by ANN modelling for varying ambient conditions. The observations on ANN results and the experimental results have shown sufficient accuracy mutually. The artificial intelligence modelling studies for this article prove the applicability of the behavioural and electrical properties of EPDM/SiR blends. These findings indicate that artificial neural networks can be a useful tool for conducting experiments on the behaviour and electrical properties of polymer materials.

KEYWORDS: Ethylene Propylene Diene Monomer (EPDM), artificial Neural Network `(ANN), Silicone Rubber (SiR), Breakdown Voltage (BDV).

تقييم سلوك شدة العزل الكهربي لخلائط المطاط باستخدام شبكة التغذية الأمامية العصبية في الظروف البيئية المختلفة

منصور محمود محمد عبدالله[١]*، لؤي سعدالدين نصرت[٢] ، علي حسن إبراهيم منصور[٢] ، السعيد عبدالعزيز عثمان[٣]

[١]قسم الهندسة الكهربائية , كلية الهندسة , جامعة الازهر, قنا , مصر

[٢]قسم الهندسة الكهربائية, كلية الهندسة , جامعة اسوان, اسوان , مصر

[٤]قسم الهندسة الكهربائية , كلية الهندسة , جامعة الازهر, القاهرة ,مصر

*البريد الاليكتروني للمؤلف الرئيسى: E-mail Mansourabdalla.2038@azhar.edu.eg

الملخص

يهدف هذه البحث إلى دراسة تأثير شدة العزل الكهربي للعازلات من مادة البوليمر المولفة من المطاط ومنها السليكون المطاطي والايثيلين بروبلين دايين مونومر في الظروف البيئية المختلفة ومحاكاة النتائج المعملية باستخدام شبكة التغذية الامامية العصبية. تم دراسة أداء العينات المختلفة من حيث مقدار شدة العزل الكهربي عند الحالة الجافة والحالة الرطبة وعند بيئة منخفضة الملوحة وأيضا بيئة عالية الملوحة. تم تحضير خمس عينات مختلفة من خلطات EPDM-SiR (٠/١٠٠ ؛ ٢٥/٧٥ ؛ ٥٠/٥٠ ؛ ٧٥/٢٥ ؛ ١٠٠/٠). تم قياس جهد الانهيار (BDV) تحت هذه الظروف البيئية في معمل الجهد العالي وفقًا لمعايير ASTM. تم استخدام البيانات التجريبية لتدريب نموذج ANN. تمثل نسبة المزج والحالة الجافة والحالة الرطبة والحالة منخفضة الملوحة والحالة عالية الملوحة الدخل لـ FFNN بينما يمثل جهد الانهيار الخرج. تمت مقارنة المخرجات التي تم الحصول عليها من ANN وفحصها مقابل البيانات التي تم الحصول عليها في المختبر. تشير هذه الدراسة إلى أنه يمكن الوثوق بـ ANN لمحاكاة تأثير الظروف البيئية المختلفة على جهد الانهيار للعينات العازلة بمعدل مرضٍ. كما يوضح أيضًا أن محاكاة ANN هي أداة فعالة يمكن اعتمادها كمرجع لتقليل الوقت والتكلفة اللازمين لإعداد العينات واختبارها في المعمل.

الكلمات المفتاحية : إيثيلين بروبيلين ديين مونومير (EPDM) , الشبكة العصبية الاصطناعية (ANN) , مطاط السيليكون (SiR) , جهد الانهيار (BDV).

1. INTRODUCTION

Polymers have been widely employed as a material in industry for a few decades, and their use is growing in a variety of engineering applications around the world. Blending is a common approach to improve the various properties of polymers used as engineering materials in electrical insulators due to its simplicity of manufacture and low cost [1]. We used the ANN model to train on the values obtained from practical experiments and raise their efficiency by reducing the error rate as much as possible by comparing the results from the model with laboratory results. This is because the artificial neural network, with its excellent features of non-linear mapping and self-adaptation, can provide an alternative to traditional methods in this work. As computational power has increased, image processing and machine learning (ML) have become popular for a number of outdoor insulator inspection applications [2-4]. This study looks into the usage of artificial neural networks (ANNs) to predict electrical performance across a wide variety of blend ratios. It focuses on modeling the impact of the blending ratio on the polymer blend's electrical properties. Only a set of labeled input-output data collected experimentally is provided as information from the blending process. Because there are no mathematical formulas to describe the process, there are few possibilities other than artificial intelligence solutions, which can build relationships between process parameters without needing to know about the process's underlying specifics. The adaptability of the artificial intelligence modeling methodology can be a very appealing component to solve this difficulty because the electrical characteristics of the blend may be dependent on process parameters and other elements that change with the experiment circumstances. In this paper, the experimental results will be utilized to examine the capability of ANNs in predicting the breakdown voltage curves and properties of pure EPDM and SiR and their blends (EPDM/SiR). The experimentally acquired data is used to train and test the neural network's performance. The key system inputs for the modeler are blend ratio and different conditions, and the system output is the breakdown voltage. The ANN predicted outputs were compared and verified against the available experimental data.

2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are a type of machine learning algorithm that learns to learn on its own by training with a large amount of data. The feed-forward back propagation neural network model was employed in this study. The FFNN model was created using the MATLAB neural network toolkit and m-file code (built-in function). Experimental data from the EPDM/SiR blending process is used as input–output data to create a model of the system. The ability of neural computing architectures to learn and adapt to changing processes and environmental situations is their strength [5]. The main component of a neural network is the neuron that performs a nonlinear weighted summation of the applied inputs as show in Fig. 1.

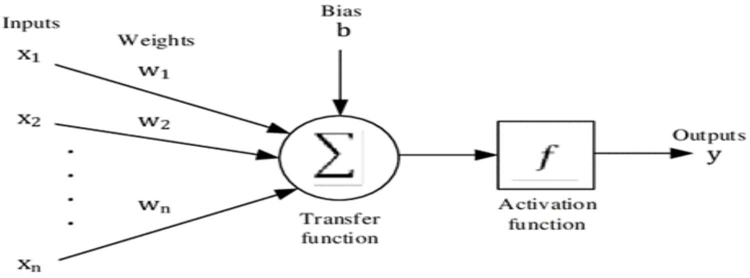

Fig. 1: The basic structure of the neuron

The network receives the input signals xi (i =1, 2,..., p inputs). They are adjusted by wji, which is the interconnection weight between input xi and neuron j, once they have been received by the neuron. To obtain a single outcome uj, all weighted inputs to a particular neuron are added together with a bias weight wjo. The result is then processed via a nonlinearity known as an activation function, also known as a transfer function, which can be a sigmoid, hyperbolic tangent, or sinh. The output of neuron j can be expressed mathematically as

$$y_j=f(W(n)Tx(n))$$

where y_j is the output of neuron j, W(n) is the interconnection weight vector, T is the transpose, X(n) is the input signal vector for iteration n, and f (•) is the activation function.

3. Experimental Tests

In the lab, the dielectric strength of five different polymer samples was examined under various environmental circumstances. For all EPDM/SiR blend ratio curves, experimental testing were done to evaluate the breakdown voltage with changes in blend ratio curves (wt percent). Various mixing processes were used at the start of the study to determine the ideal circumstances for achieving acceptable homogeneity [6-7]. The AC dielectric strength test supply and electrodes are described as follows. The AC high voltage obtained from a single phase high voltage transformer (Terco Type HV 9105) 100kV-5kVA-50Hz, has been used which is supplied by the main board from its primary. The greatest voltage that an insulating material may withstand before breaking down is known as dielectric strength. It is usually determined by the thickness of the material, the blend ratio, and the test conditions. The values are given in kV/mm. AC voltage was used to prepare and test sets of composite samples. Before beginning the high voltage test, the specimens should be dry and clean to remove dust and other contaminated particles from the surface. The dielectric strength of a sample is determined by its thickness, which is 2 mm. The samples were put through their paces utilising AC voltage in a variety of circumstances, including dry, wet, low salinity, and high salinity. As shown in Fig. 2, the voltage was steadily increased at a steady rate of 2 kV/s until voltage breakdown occurred. At dry condition ASTM-D149 [8] evaluated the test at room temperature (25°C) with a relative humidity of 51%. In wet conditions, the specimens should be placed in a container of distilled water and should be supported on edge and be completely submerged according to ASTM-D570 [9]. A salient solution of NaCl and distilled water was used to create artificial pollutants. When used underground or in submarine conditions, power delivery items (e.g. power cables) and accessories (e.g. junction, termination, and other solid dielectric components) are exposed to moisture. Water treeing causes power cables and other cable components to decay over time in a moist environment, reducing the electrical breakdown strength of the cable system[10-11]. Electrical conductivity is used to describe a measurement unit of salinity. The unit used to measure salinity is µs/cm. In this experiment, two different amount of salinity 20000 µs/cm and 50000 µs/cm are prepared.

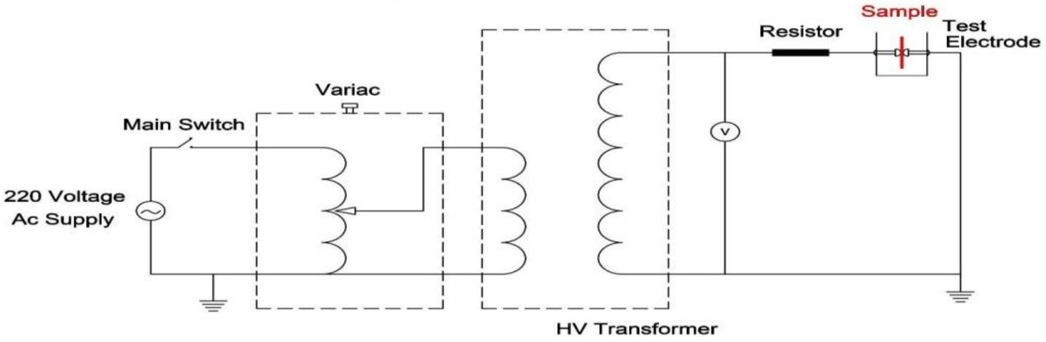

Fig. 2: Schematic diagram used for dielectric strength test

The specimens are next immersed in a conspicuous solution container at room temperature. The specimens were taken from the salient solution one at a time after 24 hours, and all surfaces were wiped clean with a dry cloth to undertake an ASTM D570 dielectric strength test.To determine the breakdown voltage properties, at least five valid results must be obtained; otherwise, the test will be repeated and any incorrect test results will be ignored. After that, the average value of the results is used. Five specimens (A, B, C, D, and E) of EPDM/SiR (wt%) mixtures/strips were obtained (0/100, 25/75, 50/50, 75/25, and 100/0). As given in Table. 1, experiments were done to evaluate the breakdown voltage under various situations (dry, wet, low salty wet, and high salty wet).

Table 1: Experimental results for the Breakdown voltage (kV) of EPDM/SiR blends at different conditions.

Test condition	Specimen NO	Percentage of EPDM blend %	Breakdown voltage kV
Dry	A	0-100	24
	B	25-75	26
	C	50-50	31
	D	75-25	35
	E	100-0	40
Wet	A	0-100	23
	B	25-75	25
	C	50-50	30
	D	75-25	34
	E	100-0	38
Low salty wet	A	0-100	21
	B	25-75	24
	C	50-50	27
	D	75-25	31
	E	100-0	35
High salty wet	A	0-100	19
	B	25-75	22
	C	50-50	25
	D	75-25	28
	E	100-0	33

4. ANN Simulation and Properties

Experimental results are used for ANN modeling and the different condition and blends ratio of the samples were determined as input parameters for ANN modeling. The feed forward neural network (FFNN) method is used to forecast the dielectric strength of untested samples for intermediate values [12]. We have a clear picture of the breakdown voltage with change in the different conditions of the EPDM/SiR mixture from previous laboratory experiments, and we have provided the experimental data used to feed the neural network with the necessary information about the behavior of the process's input and output during the learning phase. The neural network uses this stored behavior as a reference during the operation phase, when the network replicates the real operation of certain test conditions. The simulation was completed in two stages:

- In the first set, the ANN was used to predict an existing experimental data for a specific blend ratio and calculate the error percentage.
- The second set tested the capability of the ANN to prediction of a nonexistent experimental results and its location.

4.1. Step-1 Predict An existing Experimental Data.

In the first step of experiments, an ANN modeler was prepared to simulate the relationship between breakdown voltage and change in different conditions of an EPDM/SiR for blends of different ratios (0:100, 25:75, 50:50, 75:25, and 100:0 %) under different conditions (dry, wet, low salty wet, and high salty wet) based on the available experimental data. To test this, 80 percent of the data for each of the blends was used to train the network on the actual experimental data, and the remaining data was used to support the network's performance. Different conditions and the blend ratio were used as the inputs while the dielectric strength was the output as shown in fig. 3.

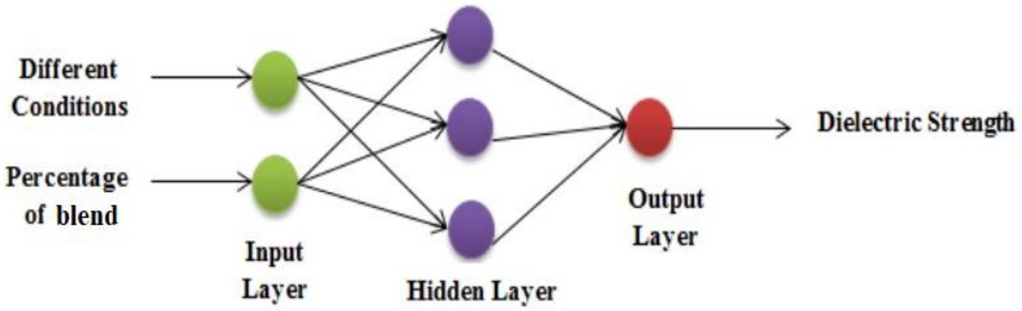

Fig. 3: The structure of inputs and output of FFNN model

Table 2: FFNN results and experimental results for the Breakdown voltage (kV) of EPDM/SiR blends at different conditions.

Test condition	Specimen NO	Percentage of EPDM blend %	Breakdown voltage kV		Error percent, %
			Experimental result	FFNN estimation	
Dry	A	0-100	24	24	0.0000
	B	25-75	26	26	0.0000
	C	50-50	31	30.5104	1.5794
	D	75-25	35	34.5004	1.4274
	E	100-0	40	39.0011	2.4972
Wet	A	0-100	23	23.7210	3.1348
	B	25-75	25	25.5323	2.1292
	C	50-50	30	30.1104	0.3680
	D	75-25	34	34.3003	0.8832
	E	100-0	38	38.411	1.0816
Low salty wet	A	0-100	21	21	0.0000
	B	25-75	24	24	0.0000
	C	50-50	27	27.0001	0.0004
	D	75-25	31	31.001	0.0032
	E	100-0	35	35.0007	0.0002
High salty wet	A	0-100	19	18.3518	3.4116
	B	25-75	22	22	0.0000
	C	50-50	25	25.1956	0.7824
	D	75-25	28	28	0.0000
	E	100-0	33	32.9999	0.0003

As shown in Table 2, once the network had converged to the preset error value, the trained network was asked to simulate the existing data, and the network's output was compared to the available experimental data to determine the network's validity. Five samples were tested for dielectric strength in dry, wet, low salty wet, and high salty wet environments. The FFNN was trained using four of them. The 5th sample was used to test the FFNN and compare it to the experimental value in order to determine the correctness of the FFNN technique and calculate the percentage of error.

$$\text{Percentage of error (\%)} = \frac{\text{Experimental value} - \text{FFNN value}}{\text{Experimental value}} \times 100$$

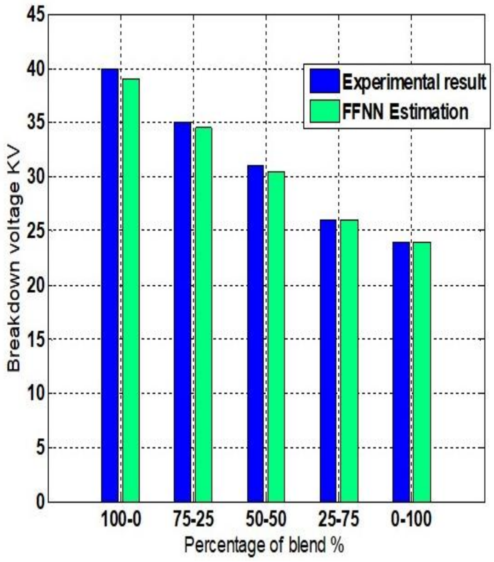

Fig. 4: Comparison of dielectric strength based on experimental results and FFNN estimation under dry conditions.

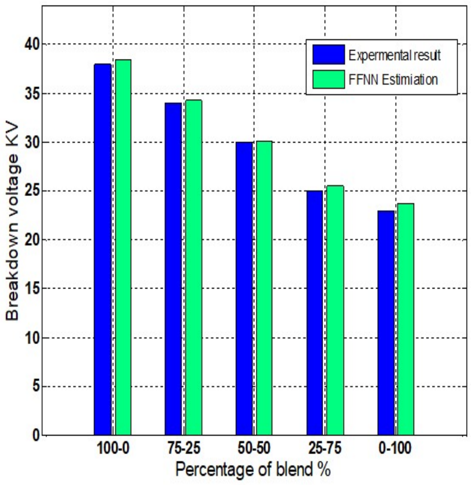

Fig. 5: Comparison of dielectric strength based on experimental results and FFNN estimation under wet conditions**,**

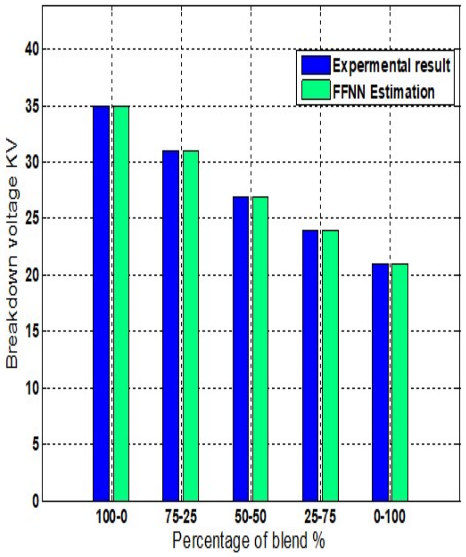

Fig. 6: Comparison of dielectric strength based on experimental results and FFNN estimation under low salty wet conditions**.**

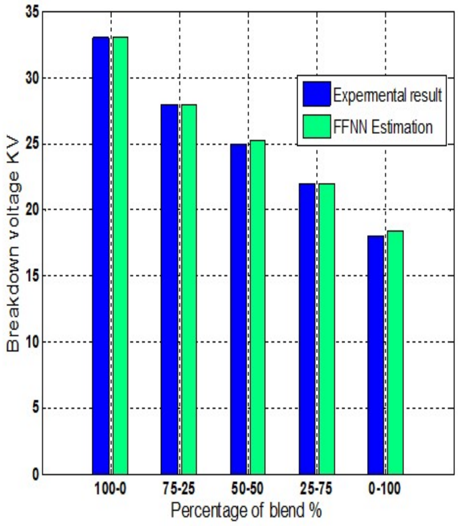

Fig. 7: Comparison of dielectric strength based on experimental results and FFNN estimation under high salty wet conditions**.**

The network was trained using the experimental data of the blend results (100:0, 75:25, 50:50, and 0:100 percent), and the trained network was asked to predict the dielectric strength results of the "25:75" blend, with the result compared to the available experimental data. It should be noted that the fifth blend results were not viewed by the network during the training phase. Table 1 and Figs 4, 5, 6, and 7 shown the predicted outcomes of this technique. The network displayed a good ability to imitate the trend of the curves, as can be shown. The network could simulate the modulus of the breakdown voltage of the blends under different condition to a high degree of accuracy as the predicted from calculation percentage of error.

4.2. Step-2 Prediction of Nonexistent Experimental Data at New Blends Under The Same conditions.

This step of experiments shows simulation of the breakdown voltage results under different condition (dry, wet, low salty wet and high salty wet) for new blending ratios (15:85,65:35,35:65 and 85:15) that fall between the available experimental data as shown in Table 3 .Simulating dielectric strength curves for blending ratios that fall between the available experimental data was the focus of the last round of tests. The simulations are quite consistent with the experimental data, as seen in figures 8, 9, 10, and 11. Such curves can serve as a useful database/information source for field knowledge.

Table 3: FFNN results for the Breakdown voltage (kV) of nonexistent EPDM/SiR blends at the same conditions

	Spacemen No	Percentage of EPDM blend %	Breakdown voltage kV
			FFNN estimation
Dry	F	15-85	24.761
	G	35-65	28.9996
	H	65-35	33.7718
	I	85-15	35.478
Wet	F	15-85	24.0327
	G	35-65	28.2761
	H	65-35	32.9761
	I	85-15	35.0351
Low salty wet	F	15-85	22.9174
	G	35-65	24.7524
	H	65-35	29.5228
	I	85-15	33.1065
High salty wet	F	15-85	20.7377
	G	35-65	23.1372
	H	65-35	27.0457
	I	85-15	29.5835

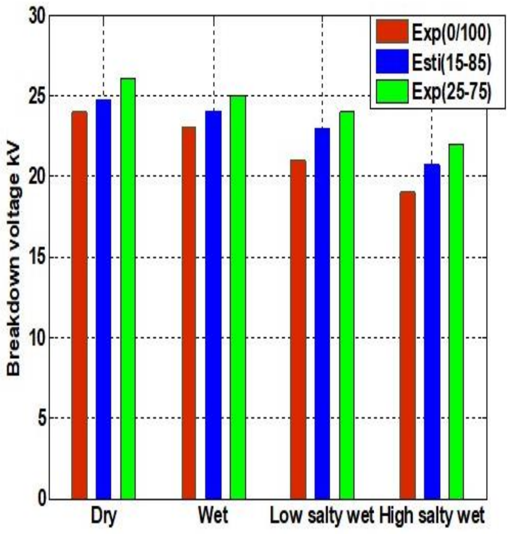

Fig. 8: Prediction of 85% EPDM curve using100 and 75 % EPDM experimental curves

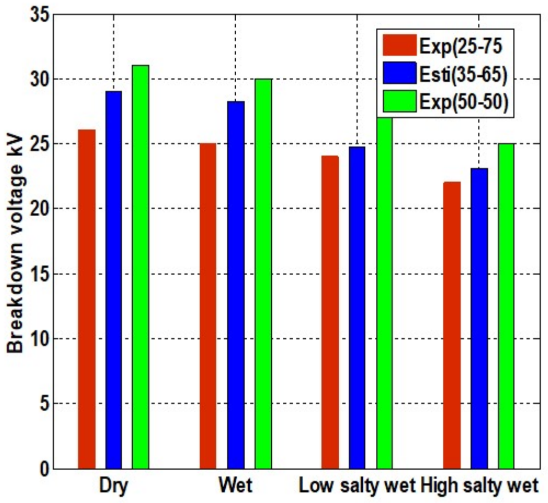

Fig. 9: Prediction of 65% EPDM curve using 75 and 50 % EPDM experimental curves

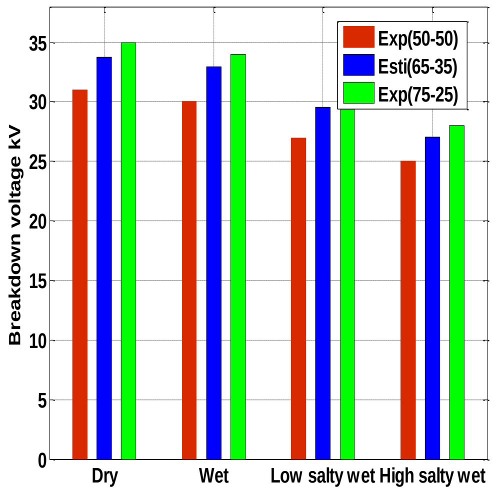

Fig. 10: Prediction of 35% EPDM curve using50 and 25 % EPDM experimental curves

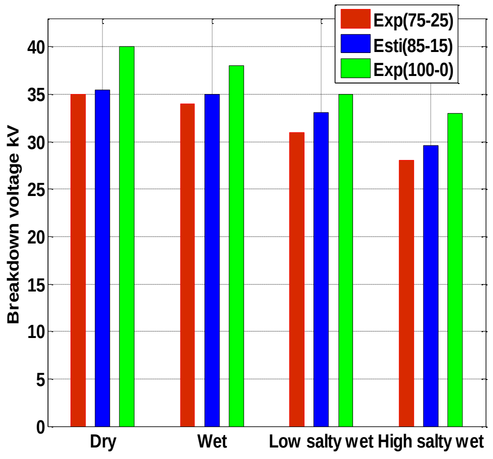

Fig. 11: Prediction of 15% EPDM curve using 25 and 0 % EPDM experimental curves

This can save time and money, as well as can simple tools and methodologies for testing the performance of polymer blends, resulting in improved and enhanced quality and properties of goods that contain polymer blends. Also, as shown in Figs. 8, 9, 10, and 11, all new blends value fall between the experimental value of 0:100 and 100:0 ratios, which are expected to provide the upper and lower boundaries for the dielectric strength curves of the different blending ratios, in the expected order.

SUMMARY AND CONCLUSIONS

The following conclusions can be achieved from this research:

1) Blending (EPDM) with (SiR) is an effective way to improve the dielectric strength.

2) Wet, low salty wet, and high salty wet environments reduced the dielectric strength of the EPDM/SiR blend when compared to dry condition.
3) The dielectric properties of EPDM, SiR, and their blends were studied using an artificial neural network technique.
4) The model was created in order to forecast the dielectric strength of an EPDM/SiR blend as the blending ratio in varied.
5) In addition, this research demonstrates how artificial intelligence modeling studies can be used in the field of polymer characterization to save cost and time.
6) These findings suggest that deep learning algorithms can be a useful tool for studying the behavior and electrical characteristics of polymer materials in the lab.

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