Predicting Insulation Thickness in Thermoplastic Extrusion Process in Nigeria Cable Industries Using Artificial Neural Network.

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***Abstract*— Cable manufacturing in a developing country like Nigeria today is faced with the problem of thermoplastic extrusion processes due to the complex nature of the parameters that are involved in the process. These process parameters that include melt temperature, pressure, and screw speed generally impact the quality of the electrical insulation product. The main consequence of the problems is the low and variable output rate from extruder causing non-uniform diameter along the cable length which often increases the production cost. Different researches have been done to improve extrusion output quality in developed countries. However, there are still some problems in achieving consistent product quality as most of the developing countries still use the trial and error techniques to determine cable insulation thickness. This paper presents a method of predicting electrical cable insulation thickness during the process of any type of thermoplastic (i.e. PVC, PE or XLPE) extrusion using an artificial neural network. A three-layered feedforward artificial neural network with back propagation algorithm was developed using MATLAB to predict the insulation thickness in thermoplastic extrusion. The neural network model developed was able to accurately predict the insulation thickness based on process parameters such as the melt temperature, pressure and line speed that have been determined in production. The possibilities of adopting neural network controllers in the thermoplastic extrusion process were also discussed.**

***Index Terms*—Artificial neural network, Cable, Extrusion process, Insulation thickness, thermoplastic**

I. INTRODUCTION

Extrusion is a process in which objects of fixed cross-sectional areas are created. It is one of the processing methods that are used in different industries such as plastic, aluminum and sheet industries. One of the most common applications of the extrusion process is in cable manufacturing. Some of the materials that are being used in cable production such as copper, aluminum, and plastic [1], primarily involve extruding to get the desired output. The machine used in the extrusion process is called an extruder.

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It processes materials by moving it along a screw and making it come out through a die at a certain temperature and pressure. One of the key components in an extruder is the screw and it is divided into three main functional zones [2]. These zones include the feed, melting/compression, and pumping. The materials which are fed into the extruder through the hopper are driven along the screw as they absorb heat that is provided by the barrel heaters. A molten flow, which occurs as a result of the heating, is then forced into the die. The die is responsible for forming the molten material into the desired shape required. Fig. 1 shows the block diagram of a typical thermoplastic extrusion process.

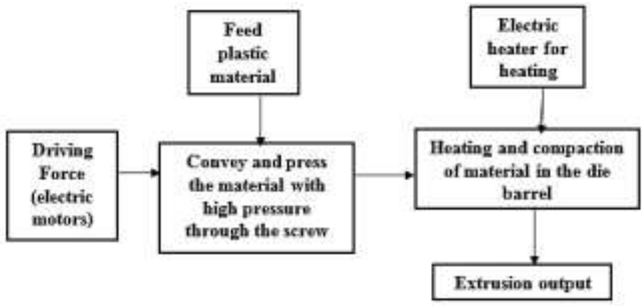

Fig. 1. Block diagram of a typical extrusion process

The melt temperature and pressure are some of the most important parameters in an extrusion process. These parameters indicate the performance, quality of an extruder. Another important process parameter includes screw speed, motor load, barrel temperature, dies temperature, the power drawn by the heaters, and the cooling rate of the cooling units. Other parameters that also affect the extrusion line include the line speed, line tension, cooling rate and the dimensions of the products being extruded [3]. Fig. 2 shows the diagrammatic representation of the components of a single screw extruder that is used in the cable manufacturing industry.

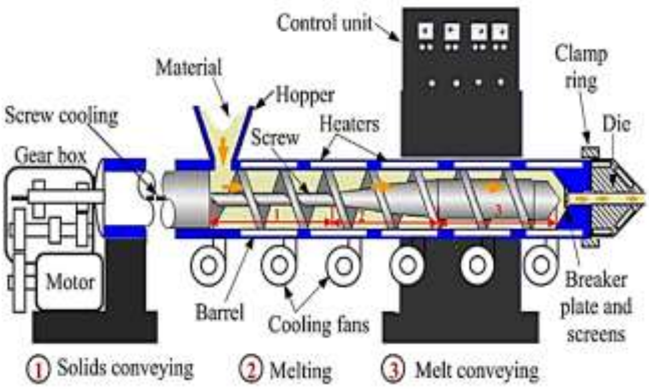

Fig. 2. Components of a single screw extruder

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In general, the production of quality output from the extruder is a major concern. For example, in cable industries, it is important that the extruder output delivers and provides a homogenous and well-mixed thermoplastic at specific melt temperature and pressure [4]. Improper operation and engineering of an extruder, however, impact the quality of the output product. This could be in the form of a defect such as cracking, voids, rough surface and thickness variations [5]. Machine learning techniques such as artificial neural network, which was inspired by the operations of the biological brain, can be applied to nonlinear systems such as the thermoplastic extrusion process. The strong learning capability, clustering, nonlinear mapping, and parallel computation capability of the artificial neural network have made it applicable to extrusion process problems. Different approaches have been taken over the years to improve and optimize the thermoplastic extrusion process in the industry. For instance, Abdulkareem et al. [6] asserted that the quality of PVC used in the cable manufacturing industry can impact the output quality from an extruder and hence, they experimentally determined the best combination of polymers with additives to produce a good quality PVC that can be extruded to produce a quality cable. These techniques are developed to ensure that the production of high-quality extrusion output is achieved while reducing manufacturing cost, downtime and waste of materials. Jing, D. et al. [7] developed a low-cost real-time energy monitoring method which is used to study the effect of process settings on efficiency and melt quality. (Zinnatullin, Kazakov, & Trufanova,) [8] investigated the use of an automatic control system in the extrusion of polymeric cable insulation. The control system developed was able to accurately determine the efficient conditions for the cooling process to some extent and hence, the production of quality cables was obtained. Abeykoon et al. [9] proposed a model-based controller that can be utilized in a polymer extrusion process to obtain a melt temperature profile prediction. Pathak, Jitendra, & Mousam, [10] investigated the effects of the process parameters in the extrusion process by utilizing the finite element method. The best process parameters for hot extrusion was also studied by Sivaprasad and colleagues [11] by using finite element simulation. Dharmendra and Sunil [12] proposed a method of optimizing the process parameters of high-density polyethylene (HDPE) material as regression analysis [13], other researchers such as Solomon and colleagues [14]; Ramya and Sreedevi [15]; and Krupal, et al. [16] have utilized the Taguchi approach to obtain great results in extrusion processes. Also, Bekir, C. [17] used artificial neural network (ANN) approach to predict the coating of thickness of wire coating extrusion processes. Rami, R., and Amin, R. [18] and Do-Hun, L. et al. [19] used application of ANN to predict XLPE cable in the extrusion process and ensemble model for simulating streamflow respectively. In the work of Mura, K. [20], a predictive ability of Bayesian regularization using ANN was applied as a comparative empirical study on social data.

In cable manufacturing industries, the materials that are required for cable production are copper (Cu) or aluminum (Al) and plastics. Polyvinyl Chloride (PVC) is the plastic that is commonly extruded and used in low voltage (1kV) cable insulation. Other types of plastics/polymers that are used in cable insulation include Polyethylene (PE), and cross-linked polyethylene (XLPE) which is suitable for medium and high voltage applications.

The melting temperature was found to be the most effective factor that contributes to the quality of the output of HDPE extrusion followed by the extrusion speed, extrusion pressure and winding speed respectively. While some have concentrated on developing control techniques using automatic control systems and nonlinear modeling techniques such and Levenberg-Marquart algorithm was applied in ANN. However, some of these approaches remain highly theoretical and do not consider manufacturing process constraints in its modeling. The breakthroughs that have been achieved with the use of ANN and machine learning can significantly improve this process. Therefore, to bridge the gap between simulations (i.e. theoretical) and real manufacturing execution systems, the use of an ANN to predict the insulation thickness of electrical cables during the thermoplastic extrusion process becomes handy. This can significantly improve the quality of the output of the extrusion process in manufacturing industries.

This paper presents a method of predicting electrical cable insulation thickness during the thermoplastic extrusion process using an artificial neural network. The possibilities of adopting neural network controllers in the thermoplastic extrusion process were also discussed. This study is organized as follows: Section 2 reviews different literature works for the techniques that have been proposed to improve thermoplastic extrusion, Section 3 describes the methods and materials that have been utilized in this work, Section 4 provides the necessary results obtained from the study and the discussion of the results obtained, and Section 5 concludes the study.

II. METHODS AND MATERIALS

A. Dataset Material

This study considered three different types of thermoplastic materials that are used in the electrical cable insulation manufacturing process. The types of cables considered in the study include Polyvinyl Chloride (PVC), Polyethylene (PE), and Cross-linked Polyethylene (XLPE) cables. The relevant data of the appropriate process parameter settings that are being used by two major cable manufacturing industries were considered. The two-cable manufacturing industry were selected based on *their capability to produce high-quality cables and ease of accessibility.* The process parameters settings that were obtained from the extrusion of PVC is shown in Table I. These parameters include the zone temperatures, *clamp temperature, neck* temperature, crosshead temperature, die temperature, line speed, melt pressure, screw speed, and the desired thickness. A 90- mm dimension of single screw extruder was used in the production of the PVC and the PE electrical cable insulation process.

Similar process parameters settings with different values were also obtained for PE and XLPE.

Table I
Production Process Parameters Settings for PVC extrusion

	Temperature in Degree Celsius												
S/N	1st Zone	2nd Zone	3rd Zone	4th Zone	5th Zone	6th Zone	Clamp	Neck	Cross head	Die	Line Speed (m/min)	Screw Speed (rpm))	Thick ness (mm)
Actual Setting	130	155	160	160	160	160	170	155	170	170	11	455	0.8
1	129	157	160	160	161	160	170	156	171	170	11	453	0.79
2	129	157	160	160	161	160	170	156	171	170	11	453	0.79
3	132	156	162	160	162	161	171	155	170	169	10	454	0.8
4	131	157	162	160	162	161	170	154	170	169	10	454	0.81
5	130	156	162	159	161	160	171	156	170	169	11	453	0.8
6	130	156	161	160	160	160	170	155	171	169	11	453	0.8
7	132	155	161	159	161	160	171	154	171	169	11	455	0.78
8	132	155	161	159	161	160	171	154	171	169	11	455	0.78
9	129	157	160	160	161	160	170	156	171	170	11	453	0.79
10	129	157	160	160	161	160	170	156	171	170	11	453	0.79
11	130	156	160	160	160	160	170	155	171	169	10	453	0.8
12	129	157	160	160	161	160	170	156	171	170	12	453	0.79
13	132	156	162	160	162	161	171	155	170	169	10	454	0.8
14	130	156	162	159	161	160	171	156	170	169	11	453	0.8
15	131	157	162	160	162	161	170	154	170	169	10	454	0.81
16	130	156	161	160	160	160	170	155	171	169	11	453	0.8
17	132	156	162	160	162	161	171	155	170	169	10	454	0.8
18	132	156	162	160	162	161	171	155	170	169	10	454	0.8
19	132	156	162	160	162	161	171	155	170	169	10	454	0.8
20	132	155	161	159	161	160	171	154	171	169	11	455	0.78
21	129	157	160	160	161	160	170	156	171	170	12	453	0.79
22	131	157	162	160	162	161	170	154	170	169	10	454	0.81
23	130	156	162	159	161	160	171	156	170	169	11	453	0.8
24	130	156	162	159	161	160	171	156	170	169	11	453	0.8
25	130	156	162	159	161	160	171	156	170	169	11	453	0.8
26	131	157	162	160	162	161	170	154	170	169	10	454	0.81
27	130	156	162	159	161	160	171	156	170	169	11	453	0.8
28	131	157	162	160	162	161	170	154	170	169	10	454	0.81
29	130	156	162	159	161	160	171	156	170	169	11	453	0.8
30	130	156	162	159	161	160	171	156	170	169	11	453	0.8
31	130	156	161	160	160	160	170	155	171	169	11	453	0.8
32	130	156	162	159	161	160	171	156	170	169	11	453	0.8
33	131	157	162	160	162	161	170	154	170	169	10	454	0.81
34	130	156	161	160	160	160	170	155	171	169	11	453	0.8
35	129	157	160	160	161	160	170	156	171	170	12	453	0.8
36	130	156	161	160	160	160	170	155	171	169	11	453	0.8
37	132	155	161	159	161	160	171	154	171	169	11	455	0.78
38	130	156	161	160	160	160	170	155	171	169	11	453	0.8
39	129	156	161	160	161	160	171	155	171	169	11	456	0.79
40	132	156	162	160	162	161	171	155	170	169	10	454	0.8
41	130	156	161	160	160	160	170	155	171	169	11	453	0.8
42	132	156	162	160	162	161	171	155	170	169	10	454	0.8
43	130	156	161	160	160	160	170	155	171	169	11	453	0.8

44	130	155	160	160	160	160	170	155	170	170	11	455	0.8
45	129	156	161	160	161	160	171	155	171	169	11	456	0.79
46	132	155	161	159	161	160	171	154	171	169	11	455	0.78
47	132	155	161	159	161	160	171	154	171	169	11	455	0.78
48	132	156	162	160	162	161	171	155	170	169	10	454	0.8
49	130	156	161	160	160	160	170	155	171	169	11	453	0.8
50	132	156	162	160	162	161	171	155	170	169	10	454	0.8
51	130	156	161	160	160	160	170	155	171	169	11	453	0.79
52	129	156	161	160	161	160	171	155	171	169	11	456	0.8
53	132	156	162	160	162	161	171	155	170	169	10	454	0.78
54	130	156	161	160	160	160	170	155	171	169	11	453	0.8
55	132	156	162	160	162	161	171	155	170	169	10	454	0.79
56	130	156	161	160	160	160	170	155	171	169	11	453	0.8
57	132	156	162	160	162	161	171	155	170	169	10	454	0.78
58	132	156	162	160	162	161	171	155	170	169	10	454	0.8
59	132	156	162	160	162	161	171	155	170	169	10	454	0.8
60	129	157	160	160	161	160	170	156	171	170	12	453	0.79

B. Artificial Neural Network

Artificial neural network (ANN) is a machine learning technique that is capable of exploring the relationships between different variables with very high accuracy. ANN has been increasing in its usage over the past decade and it is becoming very popular in solving non-linear modeling problems [21] They are composed of processing units known as neurons. These neurons consist of a group of links that are interconnected. They are known as synapses with each of them having a weight w_{kj}. The weight is multiplied by an input x_j and all the weighted weights are then summed together with an external bias b_k which is needed to increase or reduce the output of the summed data v_k. To reduce the amplitude range of the output signal y_k, an activation function φ is utilized. The neural network sequence can be represented mathematically as shown in equations (1) and (2).

$$net_k = \sum_{j=1}^{m}(w_{kj}) + b_k \quad (1)$$

$$y_k = \varphi(v_k)(net_k) \quad (2)$$

where w_{kj} is the synapses weight, x_j is the input, b_k is the bias, v_k is the sum of the weighted weights, y_k is the output, and φ is the activation function. Fig. 3 shows the model representation of a neuron.

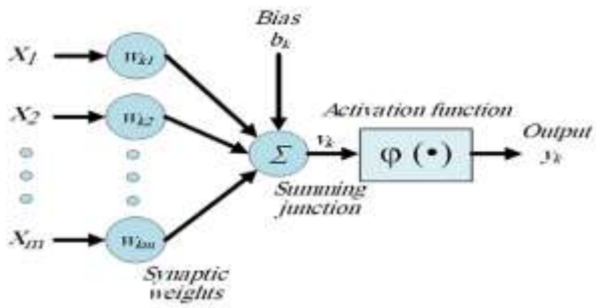

Fig. 3. Model representation of a neuron

Different types of activation functions can be used in an ANN model. Some common types include the Sigmoid linear, Gaussian and Gaussian complement functions. However, the most commonly used type is the sigmoid function and it can be expressed mathematically as shown in equation (3).

$$\varphi(v_k) = \frac{1}{1+e^{-v_k}} \quad (3)$$

In this work, the multilayer perceptron model was utilized in predicting the insulation thickness in the thermoplastic extrusion process. The multilayer perceptron which is also known as the feedforward neural network is the building block for all neural network models. It consists of one input layer, one output layer, and one or more hidden layers. Fig. 4 .

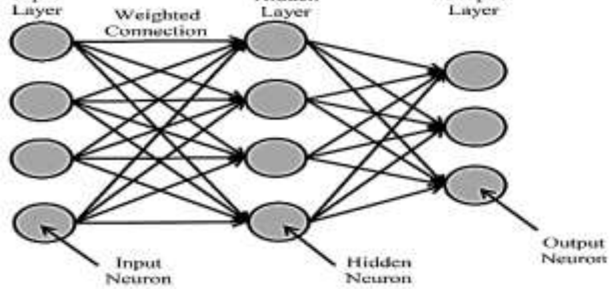

Fig. 4. Multilayer Perceptron schematic diagram

Considering that the input layer has a M set of neurons, the output of the neuron is given by equation (4).

$$Out_{i,k_i} = f\left(\sum_{m=0}^{M} w_{mk_i} x_m\right), k_i = 1, \dots, K_i \quad (4)$$

The output Out_{1,k_i} of the input neuron is also fed into the hidden neuron such that the output neuron in the hidden later is given by equation (5).

$$Out_{h,k_h} = \varphi\left(\sum_{K_{h-1}=0}^{K_{h-1}} w_{K_{h-1},k_h} Out_{h-1,k_{h-1}}\right),$$
$$k_h = 2, \dots, K_h, h = 1, \dots N_h \quad (5)$$

where φ is the activation function, K_h and M are the numbers of the hth hidden layer neuron and inputs respectively, N_h is the number of hidden layers and $w_{0,k_h}, with\ k_h = 1, \dots K_h$ are the biases of the input and hidden layers. The output layer, therefore, can be calculated by summing all the outputs of the hidden layer neurons as shown in equation (6).

$$y_t = \sum_{k_N=0}^{K_N} w_{k_h,t} Out_{N,k_N}, t = 1, \dots T \quad (6)$$

where T is the total number of neurons in the output layer, $w_{k_h,t}$ is the weight of the connecting link of the hidden layer and $k_h = 1, \dots K_h$ is the weight of the connecting link of the output layers.

The feedforward neural network is trained with a back-propagation algorithm. Training is the process in which the network is modified using an appropriate learning mode to adjust the weights to ensure that the network attempts to produce the desired output. The supervised training algorithm that was utilized in this study is the Bayesian regularization. Although the Bayesian is not the fastest training algorithm, it was selected due to its ability to provide good generalization for difficult, small, and noisy data

Structure of the Artificial Neural Network

In this study, two different ANN models were developed in MATLAB. The first model was used for both the PVC and PE materials while the XLPE was done differently due to its different configuration. Fig 5 show the network diagram of the ANN model while Fig. 6 is the function fitting neural network which are used in this study for the PVC and PE insulation thickness prediction. The MLP model consists of three layers. The input layers have thirteen (13) neurons with each neuron representing the input variables.

These input variables include the zone temperatures (1^{st}-7^{th} zone), clamp temperature, neck temperature, crosshead temperature, die temperature, line speed, and the screw speed. The hidden layer has thirty (30) neurons which were chosen based on a trial and error approach. The output layer consists of one neuron which represents the output variable. The output variable in this study is the insulation thickness.

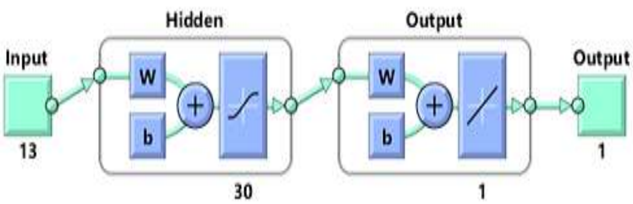

Fig. 5. Network diagram for the neural network model for PVC and PE insulations

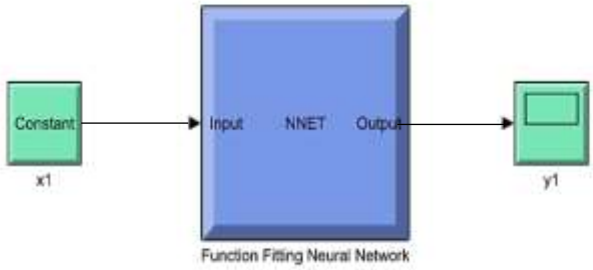

Fig. 6: Function fitting neural network

The activation function between the input and hidden layer is the tansig function while the activation function between the hidden layer and the output layer is the purelin function. Fig. 7 and Fig. 8 represent the block diagrams of the tansig and purelin functions respectively.

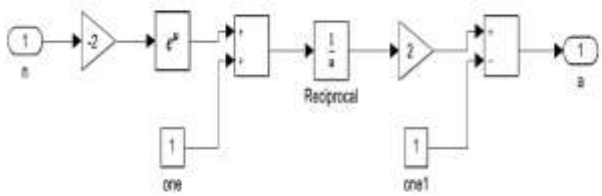

Fig. 7. Tansig activation function Simulink diagram

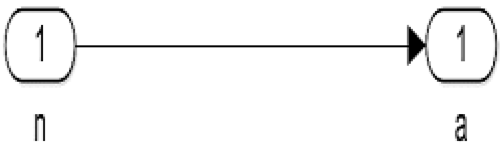

Fig. 8. Purelin function Simulink diagram

The MLP model developed for the XLPE consists of thirty-two (32) input neurons, forty (40) hidden layer neurons and one output neuron. The thirty-two input neurons consist of the different process parameters for the three extruders ranging from the zone temperatures to the caterpillar speeds. Fig. 9 shows the network diagram for the neural network model for the XLPE cables.

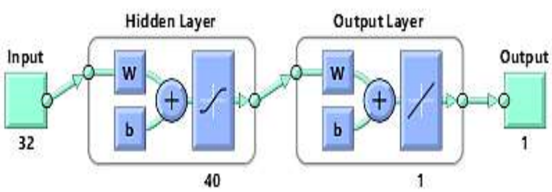

Fig. 9. Network diagram for the neural network model for XLPE insulations

The activation function between the input and hidden layer is the tansig function while the activation function between the hidden layer and the output layer is the purelin function. Eighty percent of the data that were obtained was used in training while the remaining twenty percent was used for testing the performance of the network developed in the two models at ten percent each.

The MLP schematic diagram utilized in this study is as shown in Fig. 10. The functional relationship between the independent variables (input) and the output variable can be expressed as shown in equation (7).

$$y = f(x_1, x_2, x_3, x_4 \dots x_{n-1}, x_n) \quad (7)$$

where $x_1, x_2 \dots x_n$ represent the process parameters and y represents the insulation thickness. This shows that the neural network is essentially a nonlinear regression model.

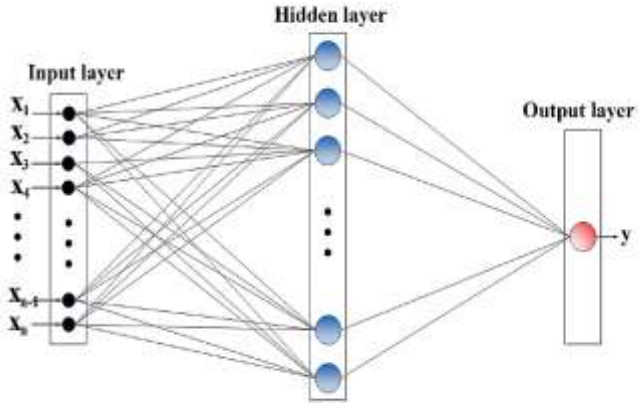

Fig. 10. Schematic diagram of the neural network model

Based on the network architecture utilized in this study, the mapping has two forms between the output and the input (independent) variables. The mapping is expressed as follows:

$$Hidden\ Layer \rightarrow n_k^{(1)} = \sum_{n=1}^{R} w_{kn}^{(1)} x_n + b_k^{(1)} \quad (8)$$

$$a_k^{(1)} = f_{1Level}(n_k^{(1)}) \quad (9)$$

$$Output\ Layer \rightarrow n_k^{(2)} = \sum_{n=1}^{R} w_{kn}^{(2,1)} a_k^{(1)} + b_1^{(2)} \quad (10)$$

$$y = a_k^{(2)} = f_{2Level}\big(n_k^{(2)}\big) \quad (11)$$

where w_{kn} are the weights of the links between the input layer and the hidden layer which are specific to independent variable n and neuron k, b_k are the biases, x_n are the input dataset, f is the activation function and y is the output. After successive iterations, the output equation can be generalized as follows:

$$y_* = f_*\big(\sum_{k=1}^{N} w_k' f\left(\sum_{n=1}^{R} w_{kn} x_n + b_k^{(1)}\right) + b^{(2)}\big); n = 1,2 \dots R\ k = 1,2 \dots, N \quad (12)$$

where w_k' is the initial weight of the link between the input layer and hidden layer, $b^{(2)}$ is the bias, and R is the total number of layers and N is the total number or neurons.

The Bayesian regularization learning algorithm utilized in this study is based on a probabilistic interpretation of the parameters of the network. In the training process and in order to compute the distance between the real and predicted data, the following function is used.

$$P = E_D(T|w, M) = \frac{1}{N}\sum_{i=1}^{n}(y_* - y)^2 \quad (13)$$

where T is the training set, E_D is the mean square error, w is the weight, y is the expected output and M is the neural network architecture. In the neural network architecture, the Bayesian regularization adds terms to regulate large weights that may be introduced in the network to obtain a smooth mapping described as presented in equations (14) and (15).

$$P = \beta E_D(T|w, M) + \alpha E_W(w|M) \quad 14)$$

$$E_W = \frac{1}{N}\sum_{i=1}^{n} w_n^2 \quad (15)$$

where E_W is the sum of the squares of the network weights, w_n is the network weigths while α and β are known as the hyper-parameters $\alpha E_W(w|M)$ is known as the weight decay and α is the decay rate. When $\alpha \ll \beta$, errors will be made smaller by the training algorithm and if $\beta \gg \alpha$, the training will reduce the weight size at the expense of the network error. This technique enables the neural network system to produce a smooth network response.

C. Performance Evaluation Criteria

To be able to validate and evaluate the performance of the neural network development, the mean square error (MSE) technique was utilized in this study. Other sets of evaluation criteria include the mean relative error (MRE), mean absolute error (MAE) and the root mean square error (RMSE). The values of the performance criteria must be close to zero (0) as much as possible to indicate the high quality of the neural network developments. The performance criteria are described with the following equations:

$$MSE = \frac{1}{n_s}\sum_{i=1}^{n_s}(d_i - y_i)^2 ; \quad (16)$$

$$MRE = \frac{1}{n_s}\sum_{i=1}^{n_s}\frac{(d_i - y_i)}{d_i} \quad (17)$$

$$MAE = \frac{1}{n_s}\sum_{i=1}^{n_s}|d_i - y_i| \quad ; \text{and} \quad (18)$$

$$RMSE = \sqrt{\frac{1}{n_s}\sum_{i=1}^{n_s}(d_i - y_i)^2} \quad (19)$$

where n_s is the number of observations, d_i is the desired values and y_i is the predicted value?

III. RESULTS AND DISCUSSIONS

In this section, the results of the study are presented. Relevant discussions are also made to enable an adequate understanding of the results obtained.

A. Predicting PVC Insulation Thickness

Table II shows the PVC extrusion dataset characteristics used in the study. It consists of the parameter number, descriptions, and some statistics such as the minimum, maximum, mean and standard deviation values of the different attributes.

Table II
Characteristics of PVC cable extrusion dataset

S/N	Description	Minimum	Maximum	Mean	Standard Deviation
Process Parameters (Input variables)					
1	1st zone temperature °C	129	132	130.639	1.096
2	2nd zone temperature °C	153	157	155.033	1.316
3	3rd zone temperature °C	160	162	161.016	0.826
4	4th zone temperature °C	159	161	160	0.775
5	5th zone temperature °C	160	162	161.115	0.819
6	6th zone temperature °C	160	161	160.443	0.5
7	7th zone temperature °C	160	163	161.344	1.124
8	Clamp temperature °C	170	171	170.607	0.493
9	Neck Temperature °C	154	156	154.934	0.772
10	Crosshead temperature °C	170	171	170.328	0.473
11	Die temperature °C	169	170	169.459	0.502
12	Line speed m/min	10	12	11.049	0.805
13	Screw speed rpm	453	456	454.443	1.025
Output variable					
1	Thickness mm	0.79	0.8	0.796	0.005

Performance Evaluation for PVC Insulation Thickness Prediction

In this study, the Bayesian regularization learning algorithm is used and training stops when the generalization stops improving. The network calculates the errors on the training and testing dataset. The neural network stops training when the error is minimized which indicates that the neural network can generalize to an unseen dataset. The regression analysis is also performed in order to measure the correlation between the target and output values. Fig. 11 shows the regression analysis plot. Table III also shows the MSE and R values for training and testing. When the regression value R is close to 1, a close relationship is indicated, however, with a regression value of 0, a random relationship occurs. It can be observed from the graphical representation in Fig. 2 that the regression values are close to 1 which indicates a close relationship between the target and the output data.

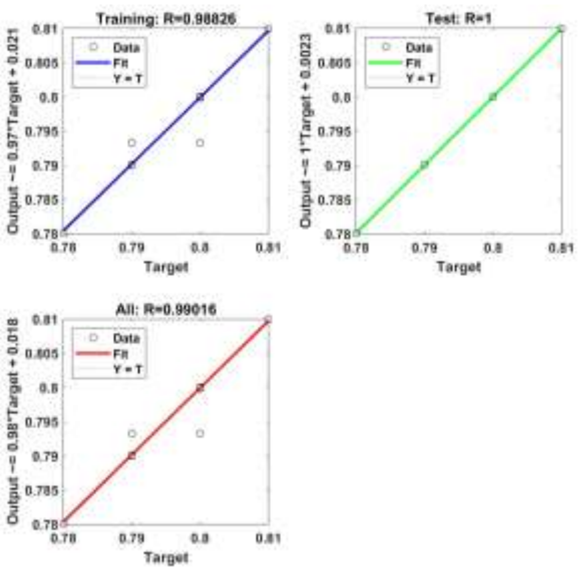

Fig. 11. Regression analysis plot for Bayesian Regularization backpropagation algorithm (PVC).

Table III
MSE and R values for the training and testing

	MSE	R
Training	1.43319×10^{-6}	0.98826
Test	1.43319×10^{-6}	1.00000
All	—	0.99016

It can be seen that the R values are closest to 1 and this indicates an accurate prediction. The performance of the Bayesian algorithm is indicated in Fig 12. From Fig. 12, it can be observed that the best training performance is 1.43319×10^{-6} at epoch 843.

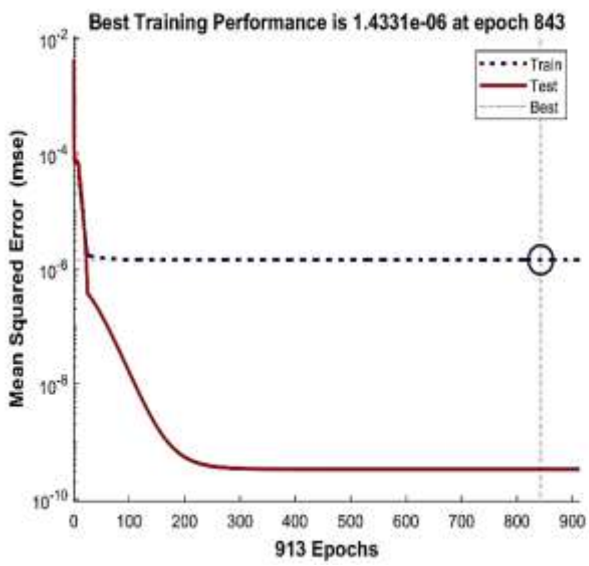

Fig. 12. Training performance for the Bayesian backpropagation algorithm (PVC).

Twenty percent of the dataset was used to validate the performance of the network. These datasets were not used in the training and act as a new dataset which can be used to determine the performance of the developed neural network model in predicting insulation thickness in the extrusion process. Fig. 13 shows the graphical representation to indicate the relationship between the production and predicted values. The mean square error (MSE) of the predicted values is obtained as 4.86965 ×10^ (-5).

It can be seen from the graph in Fig.13 that the developed neural network system can accurately predict the insulation thickness as the predicted values closely match the values obtained from the dataset used for verifying the artificial neural network system

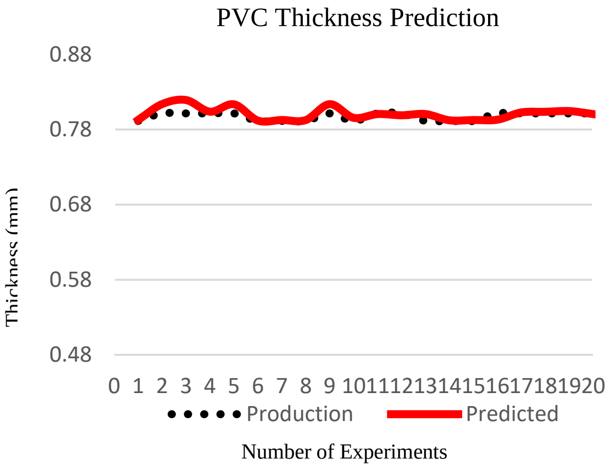

Fig. 13. Relationship between PVC predicted values and production values

B. Predicting PE Insulation Thickness

Table IV shows the PE extrusion dataset characteristics used in the study. It consists of the parameter number, descriptions and some statistics such as the minimum, maximum, mean and standard deviation values of the different attributes

Performance Evaluation for PE Insulation Thickness prediction

The production setups for the PVC and PE extrusions used in this study are the same. Hence, the network used for the PVC insulation thickness prediction was used to predict the insulation thickness for the PE cable extrusion process. Fig. 14 shows the graphical relationship between the predicted values and the production values for PE cable insulation. The mean square error (MSE) of the predicted values is obtained as 2.84315 ×10^ (-5).

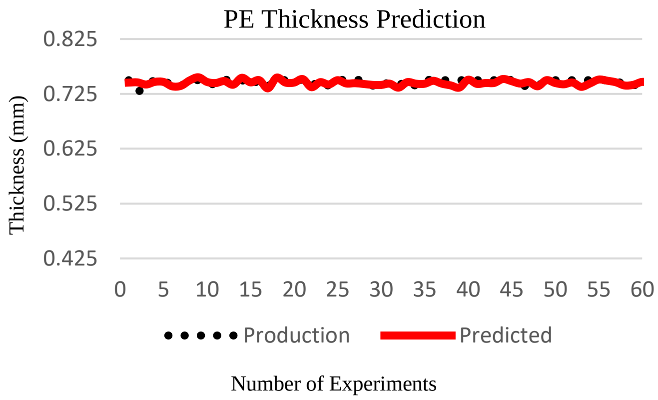

Fig. 14. Relationship between PE predicted values and production values (PE)

Table IV
Characteristics of PE cable extrusion dataset

S/N	Description	Minimum	Maximum	Mean	Standard Deviation
Process Parameters (Input variables)					
1	1st zone temperature °C	159	162	160.506	1.119
2	2nd zone temperature °C	163	167	164.656	1.389
3	3rd zone temperature °C	170	172	171.1311	0.826
4	4th zone temperature °C	175	177	176.115	0.819
5	5th zone temperature °C	180	182	180.738	0.772
6	6th zone temperature °C	184	186	185.131	0.741
7	7th zone temperature °C	190	193	191.656	1.196
8	Clamp temperature °C	194	196	195.098	0.851
9	Neck Temperature °C	194	196	195.098	0.831
10	Crosshead temperature °C	195	196	195.508	0.504
11	Die temperature °C	199	200	199.475	0.504
12	Line speed m/min	14	16	14.918	0.822
13	Screw speed rpm	171	173	172.033	0.795
Output variable					
1	Thickness mm	0.73	0.75	0.747	0.005

From the graph of Fig.14, it is observed that the predicted values of the neural network are closely related to the values obtained from the production values. The artificial neural network is capable of predicting accurately the insulation thickness from the process parameters.

C. Predicting XLPE insulation thickness

Table V shows the XLPE extrusion dataset characteristics of the dataset used in the study. It consists of the parameter number, descriptions, and some statistics such as the minimum, maximum, mean and standard deviation values of the different attributes.

Performance evaluation for XLPE insulation thickness prediction

The regression plot for the Bayesian neural network developed for the prediction of XLPE insulation thickness is shown in Fig. 15. It can be seen that the regression values are close to 1 which indicates an accurate prediction. Table VI shows the MSE and R values for the training, and testing of the neural network.

Table V
Characteristics of PVC cable extrusion dataset

S/N	Description	Minimum	Maximum	Mean	Standard Deviation
90 Extruder Process Parameters (Input variables)					
1	1st zone temperature ℃	94	96	94.803	0.853
2	2nd zone temperature ℃	100	103	101.967	1.251
3	3rd zone temperature ℃	105	107	106.131	0.695
4	4th zone temperature ℃	108	109	108.475	0.504
5	5th zone temperature ℃	110	112	110.574	0.884
6	6th zone temperature ℃	111	112	111.819	0.388
7	Setting speed rpm	118	119	118.492	0.504
8	Screw speed rpm	4.25	4.26	4.257	0.005
9	Melt pressure Mpa	14	15	14.721	0.452
10	Line Speed rpm	2.9	3.17	3.123	0.0513
11	Upper caterpillar speed rpm	258	259	258.492	0.504
12	Lower caterpillar speed rpm	258	259	258.180	0.388
150 Extruder Process Parameters (Input variables)					
1	1st zone temperature ℃	97	99	98.197	0.542
2	2nd zone temperature ℃	105	107	106.148	0.703
3	3rd zone temperature ℃	105	107	105.902	0.700
4	4th zone temperature ℃	108	109	108.25	0.437
5	5th zone temperature ℃	108	110	108.913	1.005
6	6th zone temperature ℃	111	112	111.738	0.444
7	7st zone temperature ℃	111	112	111.672	0.473
8	8th zone temperature ℃	111	112	111.409	0.496
9	9th zone temperature ℃	111	112	111.409	0.496
10	Setting speed rpm	117	119	118.574	0.644
11	Screw speed rpm	4.25	4.27	4.261	0.007
12	Melt pressure Mpa	14	15	14.262	0.444
65 Extruder Process Parameters (Input variables)					
1	1st zone temperature ℃	99	100	99.770	0.424
2	2nd zone temperature ℃	105	107	105.885	0.877
3	3rd zone temperature ℃	106	108	107.033	0.706
4	4th zone temperature ℃	111	112	111.295	0.459
5	5th zone temperature ℃	111	112	111.738	0.444
6	Setting speed rpm	133	135	133.819	0.533
7	Screw speed rpm	6.34	6.46	6.4109	0.054
8	Melt pressure Mpa	12	14	13.787	0.451
Output variable					
1	Thickness mm	0.53	0.56	0.549	0.009

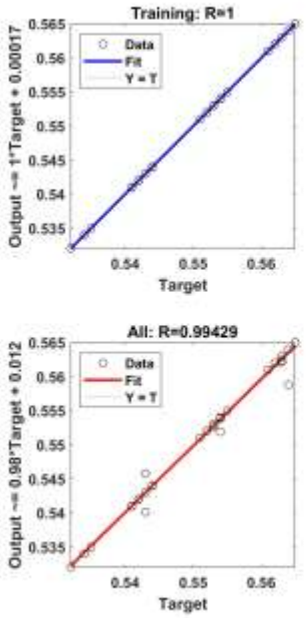

Fig. 15. Regression analysis plot for Bayesian Regularization backpropagation algorithm (XLPE).

Table VI
MSE and R values for the training and testing

	MSE	R
Training	7.8457×10^{-11}	1.00000
Test	1.99053×10^{-11}	0.96241
AII	–	0.99429

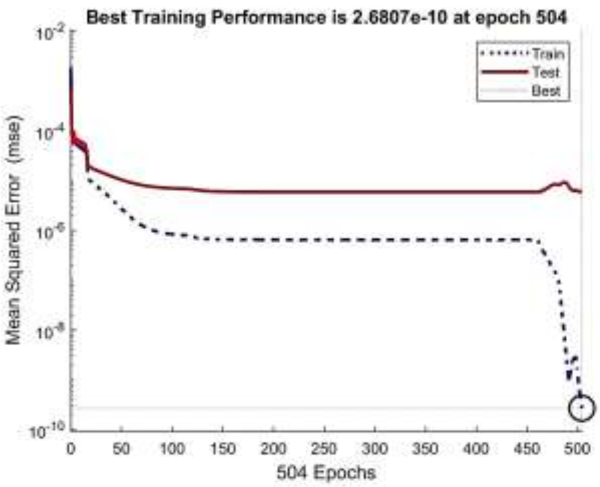

Fig. 16. Training performance for the Bayesian backpropagation algorithm (XLPE)

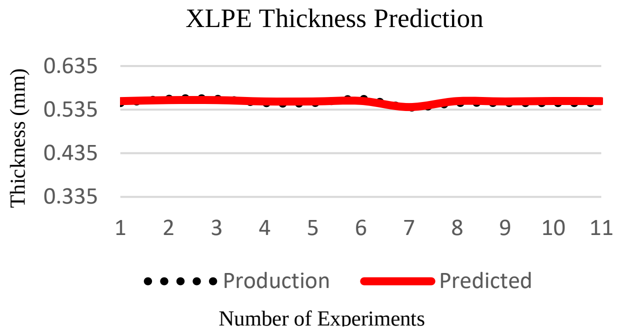

Fig. 17. Relationship between XLPE predicted values and production values (XLPE

From Fig. 16, it can be observed that the best training performance is 2.6807×10^{-10} at epoch 504. A percentage of the dataset was used to validate the performance of the artificial neural network. From Fig. 17, it can be seen that there is a close relationship between the predicted values and the values obtained from the production data set. The mean square error of the predicted values is obtained as 1.59202×10^{-5}. Hence, the system can accurately predict the insulation thickness for XLPE insulation thickness.

D. Prospects of artificial neural network in thermoplastic extrusion process

It can be observed from this study that the use of an artificial neural network can accurately predict the insulation thickness in thermoplastic extrusion. This can significantly improve the output quality and increase the production rate of electrical cables. Production managers in industries can be equipped with the appropriate tools which can enable them to produce quality cable insulation while eradicating the need to perform long experiments which can lead to waste of materials and increase the cost of production. The prospects of utilizing the artificial neural network in the extrusion process are endless as it can also be used for the control of the entire system. The neural network controller coupled with an extruder (which enables it to be able to predict future plant behaviors and select appropriate control input) which can optimize future performance.

IV. CONCLUSION

A multilayer perceptron neural network trained with backpropagation using the Bayesian regularization algorithm was developed. The artificial neural network model developed in this study was able to accurately predict the insulation thickness in the thermoplastic extrusion process for PVC, PE and XLPE cables. Before now, the use of trial and error techniques to determine the appropriate insulation thickness for cable insulation is common, but as seen in the present work, the use of artificial neural networks can eradicate the need for trial and error techniques which can improve the output quality, reduce production time and cost. An artificial neural network is best suited to solve an industrial problem because it can be applied to real manufacturing execution systems. The prospects of using an artificial neural network in the extrusion process were also highlighted. Further research work could still be done by using an artificial neural network to predict extrusion process parameters to further improve the output quality of the thermoplastic extrusion process.

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