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PREDICTING EXTRUSION PROCESS PARAMETERS IN NIGERIA CABLE INDUSTRY FOR POLYETHYLENE CABLE INSULATION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In order to obtain quality cable products in the thermoplastic extrusion process, it is important that during the polymer extrusion process, a melt that is homogenous in both temperature and composition is delivered. To achieve this, it is important to control, monitor, identify and select the important parameters during the extrusion process which directly impacts the product output. Some of these parameters include the melt pressure, temperature, line speed, screw speed, amongst others. In developing countries, however, these parameters are often selected on a trial and error basis which often leads to waste of material and the production of poor quality cables. This paper focuses on a technique which can be used to predict realistic extrusion process parameters for medium to high voltage cable insulations using artificial neural network. Real life datasets for the extrusion of Polyethylene (PE) thermoplastic were obtained and a three-layered feed-forward neural network as developed in the MATLAB environment. The neural network model developed can predict the manufacturing extrusion process parameters for different grades of PE thermoplastic which is used for medium to high voltage electrical cable insulation. A regression value of 0.99569 was obtained and a mean square error of 2.98052×10^{-6} was achieved.

Keywords: *Insulation Cables, Extrusion Process, Polyethylene, Cable Industries, ANN, Machine Learning*

1. INTRODUCTION

Electrical cables are one of the most important components that are used in the transmission and distribution of electrical power. However, in developing countries, the manufacturing of electrical cables are often faced with different challenges [1]. Some of these challenges often occur generally during the extrusion process in thermoplastic extrusion [2]. Extrusion is a process that is used to deposit a compact and uniform layer of thermoplastic (polymer) on an electrical conductor [3]. The extrusion process is not an entirely new process and it has existed for a very long period. For example, injection molding has been used in the 19th century to eject melted plastic in order to fill a mold cavity [4]. Figure 1.0 shows a block representation of an extrusion process. The extruder is divided into three main functional zones. These include the feed, melting, and pumping zones [5]. Polymer granules are passed through a hopper, and different inhibitors are added to the granules in the hopper. The granules subsequently absorb heat as through the heaters that are attached to the barrels of the extruder which produces a molten flow that is moved by a screw and pushed through a die at a particular pressure. Figure 2.0 shows the diagrammatic representation of a typical single screw extruder (Abeykoon, 2016).

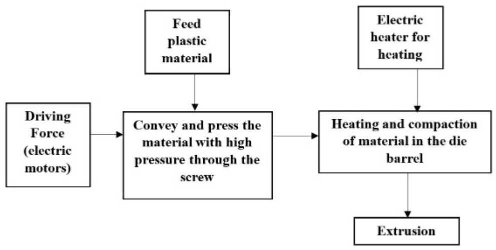

Figure 1: Block representation of the extrusion process [2]

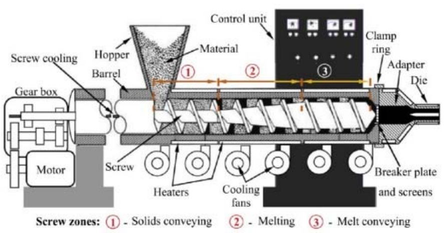

Figure 2.0: Diagrammatic representation of a single screw extruder [6].

Different types of thermoplastic materials are often extruded in cable manufacturing industries. These include the Polyvinyl Chloride (PVC), Polyethylene (PE) and the Cross-linked Polyethylene (XLPE). While the PVC is ideal for low voltage applications, PE and XLPE are suitable for medium to high voltage applications [7]. PE and XLPE are suitable for medium to high voltage applications due to their unique features which have made them suitable for cable insulation. For example, they exist in a very pure state and have a dielectric strength which is around the range of 750MV/m to 850MV/m [7]. This paper focuses on the extrusion of PE thermoplastic for medium to high voltage applications.

Due to the number of process parameters associated with the extrusion process, the process is often very complex [8]. The quality of an electrical cable is dependent on the choice of the process parameters and operating conditions [9]. Improper operations during the extrusion process often lead to the production of poor quality electrical cables [10]. Poor quality cables are often associated with defects that affect cable insulation. These defects include cracking, voids, thickness variation, etc. [1] [11]. The utilization of poor quality electrical cables can lead to different problems in electrical transmission and distribution such as insulation breakdown that can cause the loss of the life or properties. It is therefore important to develop techniques to further improve the extrusion process during electrical cable insulation [5].

In order to obtain high-quality cable production while reducing the downtime, waster of material and manufacturing cost, different techniques have been developed over the years. Different research has been done in order to improve the thermoplastic extrusion process as well as bridge the gap between simulations and manufacturing execution systems. Furthermore, non-linear modeling techniques have been utilized in order to accurately estimate the process parameters or improve the efficiency of the extrusion process [5]. Abdulkareem and his colleagues investigated the technique to improve thermoplastic material in the industry. They were able to determine that the PVC quality that is used in the cable manufacturing industries can largely affect the quality from an extruder, hence they formulated a new PVC based on locally sourced material which was used to produce quality cable insulation with reduced cost and high quality [1]. Deng et al. also introduced a low-cost energy monitoring system that is used to monitor the process settings during the extrusion process [6]. Chamil and his colleagues also discovered that energy efficiency is very vital in the extrusion process and a technique to optimize energy efficiency was presented [12]. Zinnatullin et al. and Abeykoon also presented the use of automatic control systems in the extrusion process in order to further improve thermoplastic extrusion processes [9] [10]. They were able to establish that one of the major process parameter that can greatly impact the output from an extruder is the melt temperature. The system which was developed was able to achieve the melt temperature that was desired for the thermoplastic extrusion process. The use of finite element simulation was also considered by Sivaprasad et al. in order to determine the best process parameters that can be utilized in an extrusion process [13]. The technique for utilizing process parameters for high-density polyethylene (HDPE) using the Taguchi approach was also presented by Dharmendra and Sunil. Other researchers also utilized the Taguchi approach to obtain promising results in optimizing extrusion parameters in the thermoplastic extrusion process [14] [15] [16] [17]. Regression techniques have also been used by Garcia and colleagues to predict extrusion quality in thermoplastic extrusion [18]. They also established that the quality of the extrusion process cannot be overemphasized in the manufacturing process. Other techniques such as the fuzzy logic [19], and artificial neural network [2] have been utilized to predict realistic extrusion process parameters. Abdulkareem et al. were able to accurately predict insulation thickness for electrical cable using an artificial neural network [2].

This paper focuses on predicting the extrusion process parameters for polyethylene thermoplastic material (PE) which is used in medium to high voltage electrical cables insulation using an artificial neural network.

2. MATERIALS AND METHODS

2.1 Dataset Material

This paper considered the extrusion process parameters prediction for polyethylene thermoplastic material. Relevant dataset that includes the datasheet of different grades of PE and process parameters settings were obtained from Coleman Wires and Cables, Nigeria which is one of the best cable manufacturing companies in West Africa. This company was selected based on its capability to produce high-quality cables. The complete dataset which was acquired is as shown in Table 1.0 - Table 3.0. The data consists of different process parameters settings for different grades of PE thermoplastic as well as the corresponding datasheet.

2.2 Artificial Neural Network

An artificial neural network (popularly known as ANN) has become really popular in solving different challenges in the world today. It is a machine learning technique that is developed based on the way the human brain/biological system works. ANN is capable of good generalization which simply denotes its ability to obtain outputs based on inputs that have not been encountered during training. This has made the use of ANN very crucial in solving the thermoplastic extrusion process in cable manufacturing processes. The diagrammatic representation of a neuron is as shown in Figure 3.0. It consists of input signals, synaptic weights, an adder for summing the inputs, an activation function and an output. It can be expressed mathematically as shown in equations 1 and 2.

$$v_k = \sum_{j=0}^{m} w_{kj} x_j + b_k \qquad (1)$$

$$y_k = \varphi(v_k) \qquad (2)$$

Where w_{kj} are the weights, x_j are the inputs, b_k are the biases, φ is the activation function and y_k is the output.

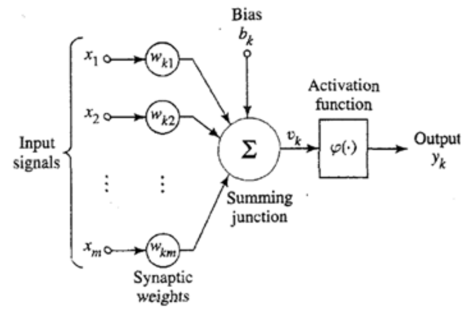

Figure 3.0: Representation of a simple neuron

The activation functions that are used in the neuron are of different types. These include the gaussian, sigmoid, and linear functions amongst others. The most commonly used type, however, is the sigmoid function. The sigmoid function is expressed in equation 3 below, The ANN model that was utilized in this study is the multilayer perceptron model generally known as MLP.

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

The MLP neural network consists of an input layer, one or more hidden layers and an output layer. Figure 4.0 shows the schematic diagram of a typical MLP neural network.

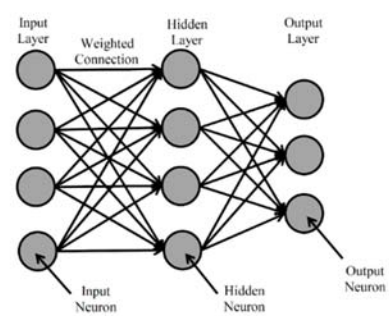

Figure 4.0: Multilayer Perceptron Schematic Diagram

Table 1.0: 30 different grades of Polyethylene dataset

Grade	P2735	P2870	P3301	P400	E803	E124	E1303	E170	E1770	PB130G1
Max Operating temp	196	187	199	190	195	190	192	195	194	192
Specific Gravity	0.953	0.95	0.956	0.969	0.928	0.925	0.925	0.925	0.924	0.905
Melt flow rate	0.06	0.09	0.09	0.06	0.08	0.09	0.09	0.09	0.06	0.06
Melt Index	0.09	0.06	0.08	0.06	0.07	0.07	0.09	0.06	0.09	0.09
Tensile Strength	23	22	14	6	7	22	14	20	19	12
Elongation at break	555	760	800	825	936	540	700	585	640	800
Softening Temperature	143	136	137	134	126	144	136	145	132	125
Melting Point	130	132	137	130	140	135	130	136	138	139
Shore Hardness, A	90	86	86	80	90	90	88	90	90	92
Stability (Thermal)	60	60	60	80	120	120	100	120	90	150
Ageing Temperature	90	80	80	80	100	100	100	100	90	100
Tensile Strength Variation	20	20	20	20	20	20	20	20	20	20
Elongation Break Variation	20	20	20	20	20	20	20	20	20	20
Profile Settings										
1st Zone	130	130	120	130	130	130	128	132	130	129
2nd Zone	145	150	135	155	150	155	145	155	150	153
3rd Zone	150	165	140	160	165	160	155	161	160	160
4th Zone	160	160	150	160	160	160	160	159	165	159
5th Zone	160	160	150	160	160	160	160	161	165	161
6th Zone	165	160	155	160	160	160	160	160	160	161
7th Zone	165	175	155	165	175	165	175	161	160	160
Clamp	170	175	160	175	175	175	175	171	172	170
Neck	155	155	160	150	155	150	155	154	155	156
Cross head	170	170	160	170	170	170	165	171	170	170
Die	170	170	155	175	170	175	170	169	180	175
Screw Speed	172	171	172	172	173	172	173	172	171	173

Table 2.0: 30 different grades of Polyethylene dataset (Continued)

Grade	PE00	PE00	CP10	CP00	PE00	PE03	2303	2202F	P1820	P2340
Max Operating temp	190	190	190	190	200	191	198	195	187	200
Specific Gravity	0.92	0.92	0.92	0.92	0.92	0.921	0.923	0.921	0.937	0.944
Melt flow rate	0.06	0.06	0.06	0.06	0.09	0.06	0.09	0.06	0.07	0.09
Melt Index	0.06	0.06	0.06	0.06	0.08	0.06	0.06	0.07	0.08	0.08

Tensile Strength	14	14	14	14	14	14	18	16	17	25
Elongation at break	500	500	500	500	500	500	400	600	750	740
Softening Temperature	123	123	123	123	143	133	125	149	149	126
Melting Point	130	130	130	130	132	135	139	137	140	135
Shore Hardness, A	90	86	86	80	90	90	88	90	90	92
Stability (Thermal)	110	90	100	80	120	120	120	150	200	200
Ageing Temperature	80	80	80	80	80	80	100	135	135	135
Tensile Strength Variation	25	25	25	20	25	20	20	20	20	20
Elongation Break Variation	25	25	25	20	25	20	20	20	20	20
Profile Settings										
1st Zone	160	160	160	160	160	160	159	159	158	160
2nd Zone	165	165	165	165	163	167	166	163	180	180
3rd Zone	170	170	170	170	172	172	172	170	180	185
4th Zone	175	175	175	175	176	176	176	177	180	185
5th Zone	180	180	180	180	181	180	182	181	180	185
6th Zone	185	185	185	185	185	186	184	186	180	185
7th Zone	190	190	190	190	193	190	192	193	180	185
Clamp	195	195	195	195	196	194	194	195	185	190
Neck	195	195	195	195	195	195	196	196	160	160
Cross head	195	195	195	195	196	195	196	196	165	170
Die	200	200	200	200	200	200	200	199	150	165
Screw Speed	170	170	170	170	172	172	171	173	172	173

Table 3.0: 30 different grades of Polyethylene dataset (Continued)

Grade	PB140	F15	WD2	D388	D477	D777	D682	L181	M1A	M30
Max Operating temp	193	197	198	181	193	199	187	187	192	193
Specific Gravity	0.905	0.92	0.96	0.919	0.943	0.921	0.932	0.938	0.938	0.932
Melt flow rate	0.09	0.08	0.08	0.09	0.06	0.08	0.09	0.09	0.06	0.08
Melt Index	0.08	0.06	0.09	0.08	0.07	0.09	0.07	0.07	0.09	0.06
Tensile Strength	14	20	20	15	17	14	20	17	14	20
Elongation at break	600	500	400	740	597	749	424	588	600	500
Softening Temperature	134	123	146	134	141	135	137	136	134	123
Melting Point	133	140	131	136	132	139	136	133	133	140
Shore Hardness, A	90	86	95	93	86	93	92	93	120	120
Thermal Stability	60	60	240	100	60	100	80	100	80	100
Ageing Temprature	80	80	135	80	80	80	80	63	20	25
Variations of TS	20	20	25	25	20	25	20	20	20	25
Variations of EB	20	20	25	25	20	25	20	20	20	20

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Profile Settings										
1st Zone	129	132	170	140	140	150	140	140	130	140
2nd Zone	153	153	180	170	150	160	160	160	150	160
3rd Zone	160	162	180	170	150	160	170	170	160	160
4th Zone	159	160	190	170	160	160	170	170	165	170
5th Zone	161	162	190	175	165	175	170	170	170	170
6th Zone	160	161	195	170	170	175	160	165	160	170
7th Zone	171	160	190	180	170	180	170	175	170	165
Clamp	155	171	200	160	180	170	170	170	160	160
Neck	170	155	180	180	170	200	160	160	180	180
Cross head	169	170	180	170	180	180	160	170	180	180
Die	175	175	180	160	190	180	170	170	190	175
Screw Speed	173	171	173	170	170	170	170	173	172	171

The MLP neural network is trained with a backpropagation 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. Different forms of training algorithms include the Levenberg Marquardt, Gradient Descent, Newton, Conjugate Gradient, and the Quasi-Newton training algorithm. The Bayesian Regularization neural network was utilized in this research. The Bayesian regularization is a training function which changes the values of the biases and the value of the weight based on the Levenberg Marquardt algorithm. The use of Bayesian regularization provides a good generalization for small data and help to solve overfitting problems [20].

2.3 Structure Description of the ANN model

This paper presents an MLP neural network for the prediction of extrusion process parameter for Polyethylene thermoplastic developed in the MATLAB. The MLP consists of three (3) layers. The input layers consist of thirteen (13) input neurons which consist of the maximum operating temperature, specific gravity, melt flow rate, melt index, tensile strength, elongation at break, softening temperature, melting point, hardness, thermal stability, aging temperature, tensile strength and elongation break variations. These data were obtained from the datasheet of different types of PE thermoplastic material which is used in the electrical cable insulation process in cable manufacturing industries. The model also consists of one (1) hidden layer with thirty (30) neurons which was chosen based on a heuristic approach and one (1) output layer with twelve (12) neurons which consists of the desired process parameters. These process parameters consist of temperature profiles from zone 1 to 7, clamp temperature, die temperature, melt pressure, as well as the screw speed. Figure 6.0 highlights the ANN model utilized in this study. Figure 5.0 shows the network diagram for the neural network for predicting extrusion process parameters for PE thermoplastic extrusion process.

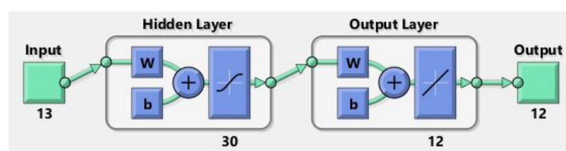

Figure 5.0: Network diagram for ANN model used for the PE extrusion process parameters prediction

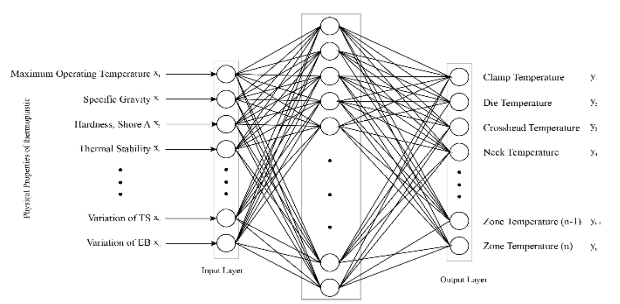

Figure 6.0: Diagrammatic representation of the neural network model

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2.4 The Bayesian Algorithm

ANN often suffer from overfitting or underfitting problems. The overfitting problem is more serious due to the fact that it can lead to the predictions of data that are not in the range of the training dataset. Overfitting generally occurs anytime a network model fits the data in the training dataset accurately, thereby leading to a large generalization error. The Bayesian regularization can be used to prevent overfitting problems. The Bayesian algorithm generally modifies the early stopping objective function shown in equation 4.

$$E_D(D|w,M) = \sum_{i=1}^{n}(t_i - \overline{t_i})^2 \quad (4)$$

$$D = \{t,(p_i)_{i=1\ldots n}\} \quad (5)$$

Where p_i is a vector input for i neurons, t is the vector output variable, w is the weights, M is a specific network architecture, and E_D is the mean square error. The Bayesian regularization modifies the objective function by adding an extra term E_w which is used to adjust large weights in order to achieve better generalization and smooth mapping. In order to minimize the modified function shown in equation 6, a gradient-based optimization technique is utilized [21].

$$F = \beta E_D(D|w,M) + \alpha E_w(w|M) \quad (6)$$

Where $E_w(w|M)$ is the sum of the squares of the architecture weights, M is a specific network architecture, α and β are hyper-parameters which takes values that will be adaptively estimated, αE_w is the weight decay and α is the decay rate which favors a small value of the weights and reduces the probability of a model to overfit. When $\alpha \ll \beta$, errors will be made smaller by the training algorithm and it $\beta \gg \alpha$, the training will reduce weight size at the expense of the network error. This technique enables the neural network system to produce a smooth network response. In neural networks, the weights are often random variables and they do not have a deep meaning before training begins, however when the training begins, the weights are updated according to Bayes' rule. The Bayes' rule is expressed in equation 7 below [22].

$$P(w|D,\alpha,\beta,M) = \frac{P(D|w,\beta,M)P(w|\alpha,M)}{P(D|\alpha,\beta,M)} \quad (7)$$

Where D is the training data, M is the neural network that is being considered, $P(w|D,\alpha,\beta,M)$ and $P(D|w,\beta,M)$ is the posterior probability and likelihood function of w respectively, $P(w|\alpha,M)$ is the old weights under M (probability of observing w), and $P(D|\alpha,\beta,M)$ is the normalization factor for α and β.

Since the normalization does not depend on w, it can be expressed as in equation 8 [21]

$$P(D|\alpha,\beta,M) = \int P(D|w,\beta,M)\, P(w|\alpha,M) dw \quad (8)$$

When the weight w is assumed to be distributed identically, the probability of observing w (joint density factor) is given as shown in equation 9 [23]

$$P(w|\alpha,M) \propto \prod_{l=1}^{m} e^{-\frac{\alpha w_{kj}^2}{2}} = e^{-\frac{\alpha E_W(w|M)}{2}} \quad (9)$$

$$P(w|\alpha,M) = e^{\frac{-\frac{\alpha E_W(w|M)}{2}}{Z_W(\alpha)}} \quad (10)$$

$$\text{Where } Z_w(\alpha) = (\frac{2\pi}{\alpha})^{\frac{m}{2}} \quad (11)$$

Since target variable t is a function of the input variables p, this relationship can be modeled as $t = f(p)$. Therefore, the joint density function for target variables based on provided input variables β and M is expressed in equation 12.

$$P(t|p,w,\beta,M) = \frac{\beta}{2\pi}^{\frac{N}{2}} e^{-\frac{\beta}{2}\sum_{i=1}^{N}(t_{i-}f(p_i)^2)} \quad (12)$$

$$P(t|p,w,\beta,M) = \frac{\beta}{2\pi}^{\frac{N}{2}} e^{-\frac{\beta}{2}E_D}(D|w,M) \quad (13)$$

The posterior density in equation 7 can be modified with the equations above. If $Z_D(\beta) = \int e^{-\frac{\beta}{2}E_D}(D|w,M) = (\frac{2\pi}{\beta})^{\frac{N}{2}}$, the modified posterior density equation can be expressed as in equation 14 [23].

$$P(w|D,\alpha,\beta,M) = \frac{\frac{1}{Z_\pi(\alpha)Z_D(\beta)} e^{-\frac{1}{2}(\beta E_D+\alpha E_W)}}{P(D|\alpha,\beta,M)} = \frac{1}{Z_F(\alpha,\beta)} e^{-\frac{F(w)}{2}} \quad (14)$$

Where $Z_F(\alpha,\beta) = \left(Z_w(\alpha)Z_D(\beta)\, P(w|D,\alpha,\beta,M)\right)$ and (15) $F = \beta E_D + \alpha E_W$ (16)

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In the Bayesian regularization, the neural network model chooses the best weights which can optimize the posterior density $P(w|D, \alpha, \beta, M)$ which is similar to minimizing the regularized objective function F in equation 16. Obtaining the minimum value of the objective function F is similar to finding a posteriori estimate denoted as w^{MAP} and the minimization of E_D is identical to finding the maximum estimate denoted by w^{ML}. The use of the Levenberg Marquardt can be adopted to locate the lowest value of F [24]. The modification of the Gauss-Newton algorithm by the Levenberg Marquardt optimization is as seen in equation 17.

$$(\mu I)\delta = J'e \quad (17)$$

The Hessian matrix is approximated as

$$H = J'J \quad (18)$$

Where J is the Jacobian matrix, μ is the Levenberg damping factor, and δ is the parameter update vector. The parameter update vector simply indicates the degree at which the values of the weight is needed to be altered to obtain a better prediction. The Jacobian matrix (a partial derivative of the output with respect to the weight) J has the form:

$$J = \begin{bmatrix} \frac{\partial e_1(w)}{\partial w_1} & \frac{\partial e_1(w)}{\partial w_2} & \cdots & \frac{\partial e_1(w)}{\partial w_n} \\ \frac{\partial e_2(w)}{\partial w_1} & \frac{\partial e_2(w)}{\partial w_2} & \cdots & \frac{\partial e_2(w)}{\partial w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_N(w)}{\partial w_1} & \frac{\partial e_N(w)}{\partial w_2} & \cdots & \frac{\partial e_N(w)}{\partial w_n} \end{bmatrix} \quad (19)$$

The stepwise algorithm that is utilized by the Bayesian regularization learning algorithm is clearly highlighted below. Figure 7.0 also shows the flow diagram of the algorithm. (1) Use the Levenberg Algorithm to reduce the objective function and obtain the present value of w. This is done by computing the Jacobian matrix, error gradient, Hessian matrix, and the objective function before the weight are updated. (2) Compute the effective number of parameters using the LM algorithm. (3) Compute the new hyper-parameter values. (4) Repeat steps 2-4 until convergence.

2.5 Performance Evaluation Metric

Evaluating the performance of the developed neural network model is very important in order to ensure that the model developed is very good. Different performance indices that can be utilized include the mean square error, mean relative error, mean absolute error, mean accuracy percentage error. The mean squared error, popularly known as MSE was utilized in this study. Equation 20 shows the mathematical expression for the MSE performance metric.

$$MSE = \frac{1}{n_s}\sum_{i=1}^{n_s}(d_i - y_i)^2 \quad (20)$$

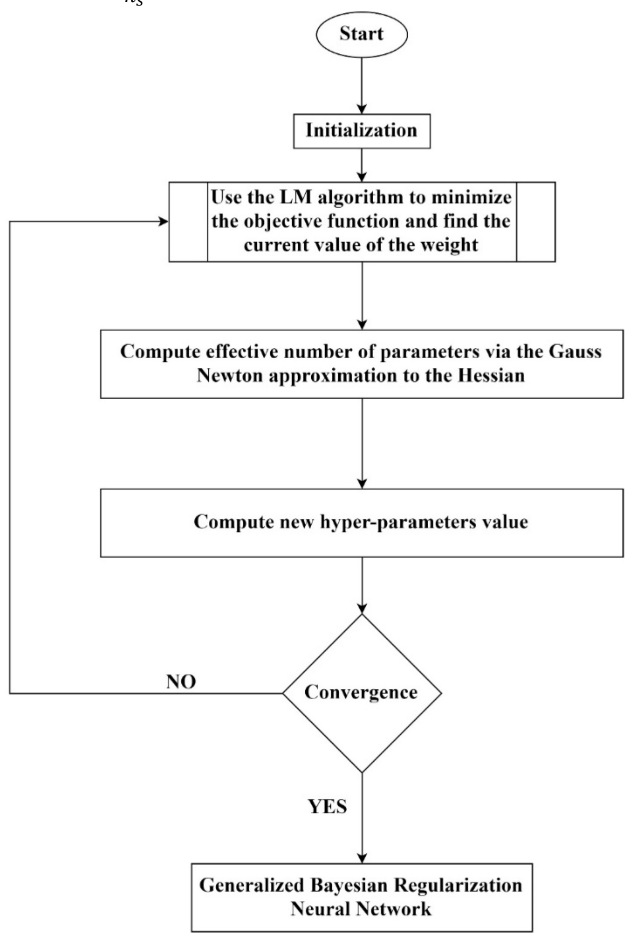

Figure 7.0: Flow diagram of the Bayesian Regularization Neural Network

2.6 System Specification

A computer system running a Windows Operating System with a memory of 8GB RAM was utilized in this study. The MATLAB software by MathWorks was used to develop the ANN model using inbuilt features such as the neural network toolbox which was used in this paper. Its graphical output is optimized for interaction, good data plotting tools in different colors, sizes, and scales.

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3. RESULTS AND DISCUSSIONS

The results obtained from the work in this paper are presented in this section. Necessary tables, figures and accompanying graphical representations are also presented. The results were also discussed and important points were clearly highlighted.

3.1 Predicting Extrusion Process Parameters for PE thermoplastic material

Table 4.0 shows the design summary for the MLP model that was utilized in the study. Thirty (30) different grades of PE thermoplastic was obtained in which about 80% was used for training the neural network and the 20% was used for validation and testing the neural network.

Table 4: Multilayered Perceptron neural network design approach.

Material	PE
Number of data	30
Training data	26
Validation data	4
Training Method	Bayesian Regularization
Activation Function	Purelin and Tansig
Training Time	10 seconds
Number of Iterations	600
Performance Evaluation	MSE
Number of Inputs Layers	1
Number of Input Neurons	13
Hidden Layers	1
Hidden Neurons	30
Output Layer	1
Output Neuron	12

The regression plot for the MLP model is as shown in Figure 8.0. The regression plots clearly show the regression values (R values) for the training and testing dataset. Table 5 also shows the mean squared error (MSE) and R-values for the developed model. It can be observed that the R-values are very close to 1 and the mean squared error is very low which invariably signifies a very good model. This indicates that the model developed is capable of accurately predicting the extrusion process parameters for PE thermoplastic extrusion process.

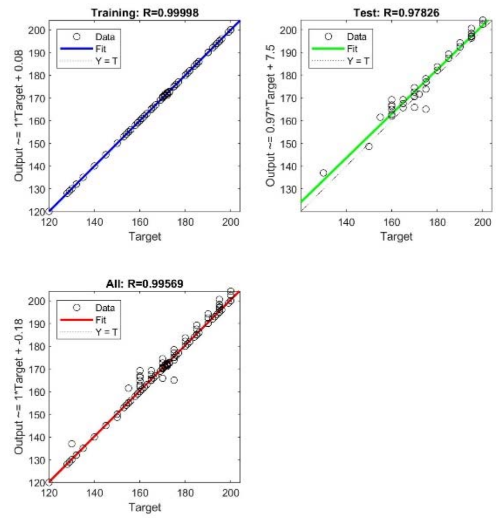

Figure 8.0: Regression analysis plot for Bayesian Regularization (PE process parameters).

Table 5: MSE and R-value for the training and testing

	Mean Squared Error	Regression
Training	8.54430×10^{-11}	0.99998
Test	2.98052×10^{-6}	0.97826
All	-	0.99569

Four (4) different grades of PE which were not used in the training of the neural network was used to determine the performance of the neural network developed. The model that was developed can predict the process parameters for different PE thermoplastic material. The relationship between the actual and the predicted values are presented in Tables 6 and 7. The graphical relationships are also presented in Figures 9 to 12. A close relationship between the actual and the predicted values can be observed in the relationship table and graphical representations.

It can be observed from the results that the artificial neural network is capable of predicting the extrusion process parameters for different grades of PE thermoplastic extrusion process. This technique can really improve the production of quality electrical cables by enabling production managers to

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be equipped with the right tools to produce high-quality cables.

Table 6: Differences between the predicted and production values for M30 and M1A

Name	M30			M1A		
Settings	Actual Value	Predicted Value	Error	Actual Value	Predicted Value	Error
1st Zone	140	140.874	-0.87359	130	133.421	-3.42093
2nd Zone	160	165.543	-5.54338	150	154.667	-4.66665
3rd Zone	160	161.797	-1.79724	160	159.277	0.722649
4th Zone	170	166.355	3.644722	165	166.189	-1.18879
5th Zone	170	169.075	0.925284	170	168.119	1.881291
6th Zone	170	167.093	2.907409	160	161.32	-1.31982
7th Zone	165	164.15	0.849624	170	167.265	2.734684
Clamp	160	154.657	5.343137	160	157.717	2.283157
Neck	180	182.265	-2.26505	180	179.402	0.598131
Cross head	180	174.14	5.86047	180	180.762	-0.76151
Die	175	173.6919	1.308136	190	187.3623	2.637666
Screw Speed	171	170.5832	0.416815	172	171.1655	0.834487

Table 7: Differences between the predicted and production values for L1810F1 and D682PC

Name	L1810F1			D682PC		
Settings	Actual	Predicted	Error	Actual Value	Predicted	Error
1st Zone	140	140.26	-0.26018	140	136.35	3.650402
2nd Zone	160	163.981	-3.98057	160	161.84	-1.8401
3rd Zone	170	171.156	-1.15586	170	171.129	-1.12894
4th Zone	170	167.872	2.127889	170	167.423	2.577056
5th Zone	170	168.496	1.503746	170	167.602	2.398219
6th Zone	165	165.546	-0.54635	160	161.185	-1.18509
7th Zone	175	174.253	0.746952	170	167.016	2.983731
Clamp	170	172.025	-2.02538	170	169.625	0.375336
Neck	160	161.932	-1.93181	160	152.2	7.799841
Cross head	170	169.472	0.528084	160	165.201	-5.20077
Die	170	170.5028	-0.5028	170	168.0235	1.976487
Screw Speed	173	171.046	1.953973	170	170.7827	-0.78274

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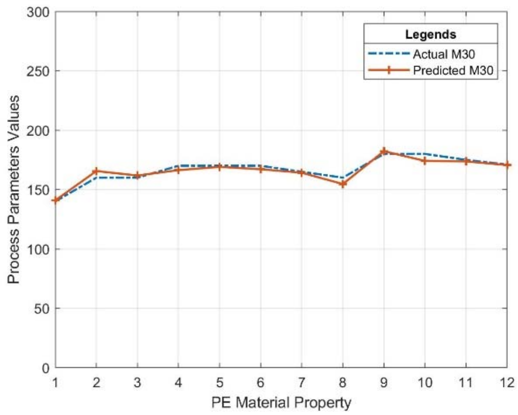

Figure 9: Graphical relationship between actual and predicted values (M30)

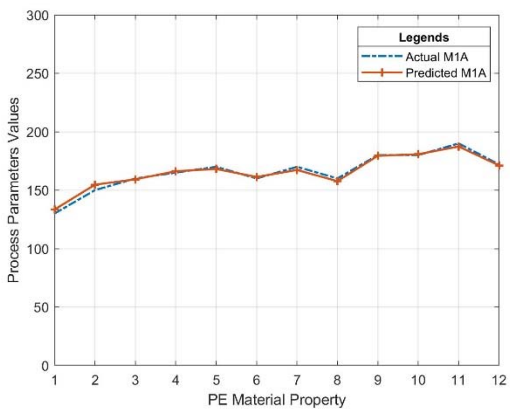

Figure 10: Graphical relationship between actual and predicted values (M1A)

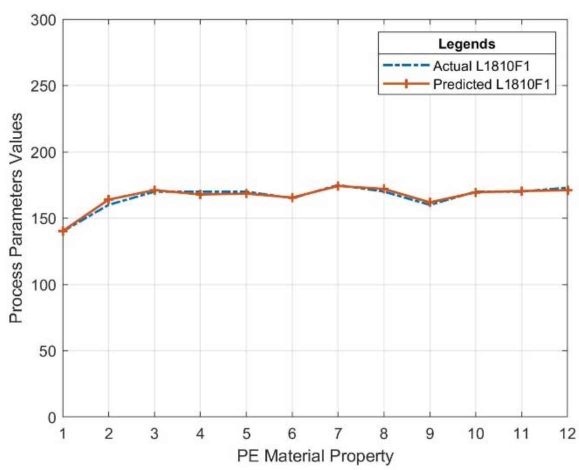

Figure 11: Graphical relationship between actual and predicted values (L1810F1)

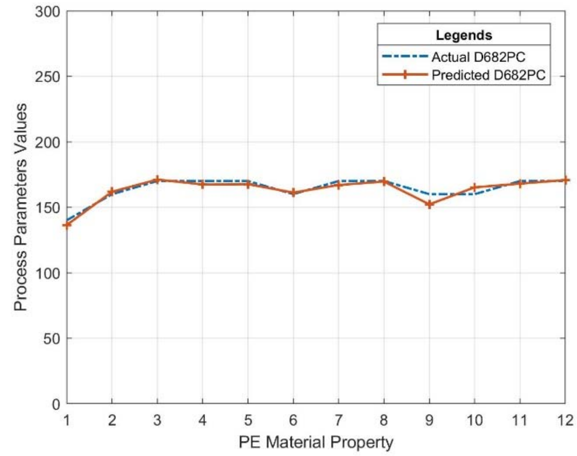

Figure 12: Graphical relationship between actual and predicted values (D682PC)

4. CONCLUSION

This paper presents a technique that can be used to predict extrusion process parameters for PE thermoplastic extrusion process which is useful for electrical cable insulation for medium to high voltage applications. A multi layered network which was trained with the Bayesian regularization technique was utilized. The paper shows that the developed ANN model is can predict extrusion process parameters for different grades of polyethylene material. This technique can be incorporated into manufacturing processes in order to improve the production of high-quality electrical cables. The use of trial and error techniques can be eradicated in the thermoplastic extrusion process, which generally will improve the efficiency in cable manufacturing processes. Further research work can still be done in order to further improve the thermoplastic extrusion process by integration neural network controllers to further solve industrial problems.

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