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In Process Density of HDPE Pipe Material Prediction Using Artificial Neural Network in a Polymer Extruder

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***Abstract*—The pipe extruder process from the traditional pipe products. The model is based on three layer neural network with back propagation learning algorithm. The training data are collected by the experimental setup in the laboratory. The predicted density of neural network model, coincide well with the experimental density. A three layer artificial neutral network ANN model was used for the description of extrusion density. The studies employ experimental data obtained from capillary flow experiments using HDPE molten. On comparing the experimental data, the predictions using the ANN model predictions; it is found that the ANN model is capable of predicting the extrusion density well. The neural network model shows how the significant parameters influencing pipe material density can be found. A three layer multi-layer perceptron artificial neural network was used to correlate the response of the densitymeter to the measured molten density. The density of the extruded pipe was varied by varying the processing conditions over a wide practical range. In this study, an artificial neural network approach for exploring the prediction of the pipe extruder process parameters, molten HDPE density of pipe extrusion product is derived.**

***Keywords*—Density; HDPE; Pipe; Extrusion; ANN**

1. Introduction

The objective of this work is to develop a correlation between the measured properties of the extruded polymer melt and the density of the pipe material. A robust in line monitoring technique can provide plastics manufacturers with the ability to respond to material and process variations accurately and fast in order to maintain the quality and cost of the extruded material within specifications. In addition, a real-time monitoring technique can help to automate many of the plastics manufacturing processes; therefore minimizing the need for the scarce highly skilled machine operators.

In pipe extrusion processes, product density is considered to be the most significant factor affecting the production cost and profitability of the manufacturing process. Density of HDPE (High Density Poly Ethylen) can be controlled by varying the type and amount of compound additives, processing parameters, or both [1]. Compound additives; such as blowing agent, nucleation agent, and process aid have a significant effect on the foam density and their effect was shown to be interrelated [2]. Processing parameters such as the temperature of the barrel's heating zones and screw speed have also shown a considerable effect on the foam density [3]. Many publications have presented studies on the design and performance of foam extrusion processes [4–7].

Artificial neural network (ANN) models have been studied in recent years, with an objective of achieving humanlike performance in many fields of knowledge engineering. Neural network applications are growing rapidly as artificial intelligence tools in the area of speech recognition, pattern recognition, and in robotics and communication [8].

2. Material and experimental procedure

The densitymeter is installed at the exit end of the extruder. The connecting of densitymeter and transducers is similar to the capillary rheometer as shown in Fig. 1. The melt density is measured basing on the measurement of the pressure drop and the flow rate through the process line. Single pressure and temperature transducers are installed in the barrel to measure the pressure and temperature.[9]

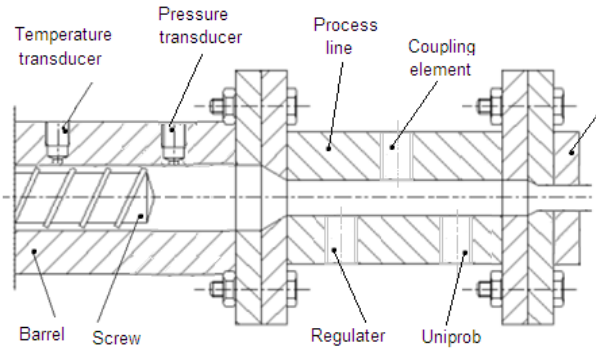

Figure 1. Connecting of densitymeter and transducers

In this experimental study used pipe extruder and compartments. This equipment is shown in Fig. 2. Therefore the means of compartments are follows; A- Extruder motors, B- Coupling elements, C- Barrel and three heater zones, D- Densitymeter, E- Hopper, F- Command panels.

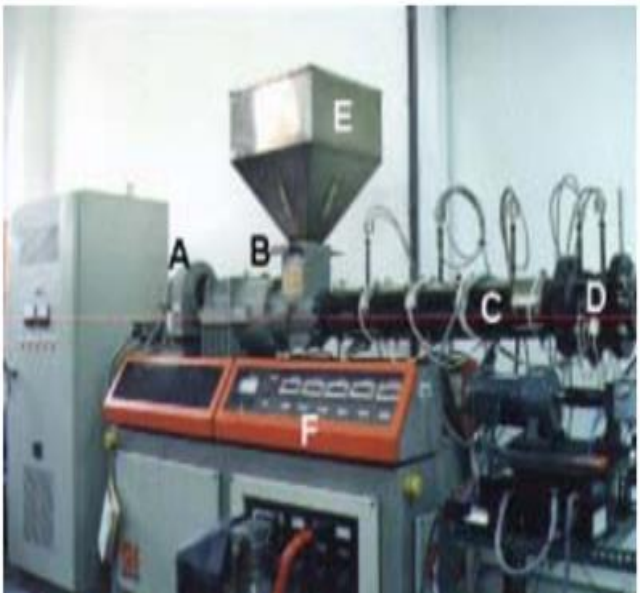

Figure 2. Pipe extruder and compartments

The density of the pipe material has been obtained by measuring the dimension and weight. HDPE (High Density Poly Ethylene) natural and setting density is 0.95-0.96 g/mL. Experimental density values are connected by densitymeter (uniprobe LB 491) in laboratory of MARDİN PİPE CO.

Fig.3 Shows this systems of density measurement. High density polyethylene plastic pipe (HDPE) delivers exceptional value, unwavering reliability and remarkable advantages over conventional types of piping. It's today's right choice for density measurement of plastic materials.

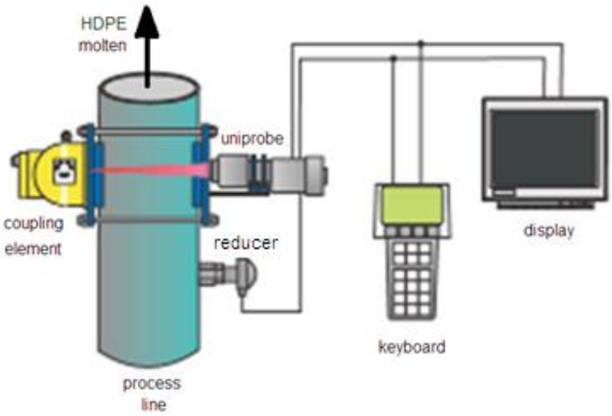

Figure 3. Densitymeter (uniprobe LB491) in Laboratory of MARDİN PİPE CO.

The technological parameters such as pressure, temperature of HDPE and screw speed are input variables and the measured pipe material density of piping extruder process is the output parameter. In this section 120 pairs of experimental data points under different process condition were collected out of which 60 data points were used to train the neural network and the remaining 60 data points were used for testing the neural network, the sample data is shown in Table 1.

Table 1. Some of sample data for planning the neural network model

HDPE Pressure (kg/mm^2)	HDPE Temperature (°C)	Screw Speed (rpm)	HDPE Density (gm/cc)
12.5	155	40	0.950
15.5	160	45	0.955
15.5	180	50	0.952
19.0	175	55	0.957
21.0	195	40	0.958
12.5	200	55	0.959
15.5	150	50	0.951
12.5	160	45	0.952
15.5	195	45	0.960
19.0	190	40	0.956
21.0	180	50	0.954
12.5	155	55	0.955
15.5	170	40	0.959
15.5	195	55	0.960
15.5	185	50	0.952
12.5	165	45	0.953
15.5	150	40	0.951
19.0	170	40	0.956
21.0	185	55	0.954

3. Back propagation neural network model and principle

In this study a three layered back propagation neural network is applied to predict the sinter-forged density of metal powder preform. The proposed neural network (Fig. 4.) contains three layers, input layer (3 neurons) output layer (1 neuron) and one hidden layer (7 neurons). A C + + source code has been compiled for training and testing the proposed back propagation neural network. The developed neural network is trained with the training data set until the desired error limit is reached, then the connection weights are stored in a text file and is further used for testing the developed neural network.

The most frequently used and effective supervised learning algorithm known in the world of neural networks is the back propagation neural network. The fundamental theory and applications of back propagation neural network were reviewed by many researchers. The network consists of three groups of nodes, namely, an input layer, hidden layers and an output layer. Fig. 4. shows an example of the structure of a feed forward network with three input, seven hidden and one output layer.

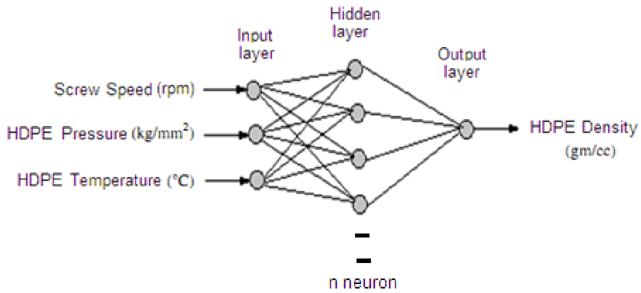

Fig. 4. Structure of Density ANN Model

The three layers are fully connected with five nodes in the input layer, four nodes in the hidden layer and one node in the output layer. This network can be termed a 3-7-1 feed-forward network, referring to the number of nodes in the input, hidden and output layers, respectively. All the nodes are allowed several input signals and only one output signal, just as a biological neuron. Scaled data usually scaled to the range of 0–1 is introduced into the input layer of the network and then is propagated from input layer to hidden layer and finally to the output layer. The nodes in the input layer act only as a buffer, sending out scaled inputs to the hidden layers (Fig. 5.). In the hidden layers and output layer, each node firstly acts as a summing junction which combines and modifies the inputs from the previous layer using:

$$y_j = \sum_i x_i w_{ji} + \theta_j \quad (1)$$

where y_j is the total weighted input of the j th node in the layer, say layer L, x_i is the output of the i th node in thei previous layer, say layer L-1, and w_{ji} is the weight representing the strength of the connection between the i th node and j th node while θ_j is a threshold value.

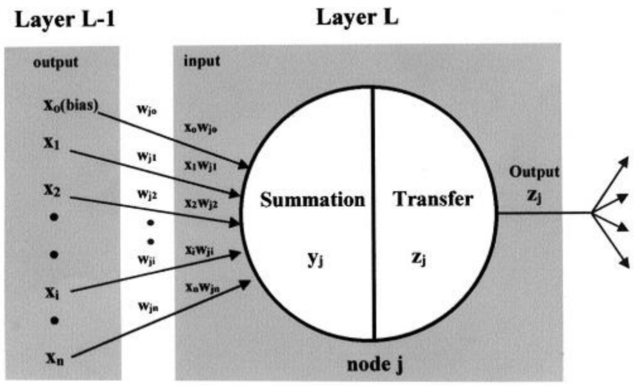

Fig. 5. Base of single artificial neuron

Then each node transfers the summation y_j to the output of the j node z_j through, typically, a sigmoid function:

$$z_j = \frac{1}{1 + e^{-y_j}} \quad (2)$$

z_j , the output of node j, is also an element of the inputs to the nodes in the next layer.

The values of the interconnection weights are deter-mined by a neural network training or learning procedure using a set of data. The objective is to find the value of the weight that minimizes differences between the actual output and the desired output in the output layer. The back propagation algorithm firstly adjusts weights connected to the output layer. Then, working backward towards the input layer, the algorithm adjusts weights in each successive layer to reduce the errors at each level. The delta learning rule is one of the well-known weight update rules, which is based on the simple idea of continuously modifying the strengths of the connections to reduce the difference the delta between the desired output value and the current output value of a processing element. It is expressed as:

$$\Delta w_{ji}(n+1) = \eta d_j x_i + \mu \Delta w_{ji}(n) \quad (3)$$

where w_{ji} is the connection weight between nodes i and j, n is discrete time cycle number , η is the learning rate, d_j is the difference between actual and predicted values, x_i is the current output of processing element i and μ is momentum factor. The larger the learning rate, the larger the weight changes on each epoch (training cycle), and the quicker the network learns. However, the size of the learning rate can also influence whether the network achieves a stable solution. The concept of momentum is that previous changes in the weights should influence the current direction of movement in weight space. The effect of the learning rate and the momentum on network performance was discussed by Li and Bridgwater [10].

A neural network model with a back propagation algorithm was employed for the network training and simulation in MATLAB 2014 b program. The model was firstly constructed by determining the number of nodes and layers. The number of nodes in the input layer is dependent on the requirement of the simulation.

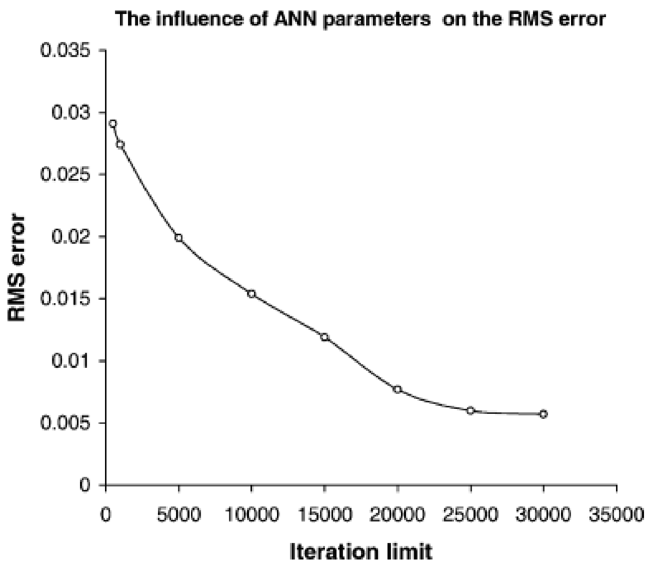

Fig. 6. Iteration number versus mean RMS error for training nonlinear pipe material density

From Fig. 6. it is evident that, for a smaller number of training iterations the RMSerror has been found to be quite high. Once the optimum number of training iterations is reached, the RMS error is found to be minimum. Even though the number of training iterations is increased beyond the optimum number of training iterations, there is no significant improvement in the prediction accuracy. An ideal or optimum coefficient is momentum factor μ= 0.8, learning rate η= 0.9 and hidden layers= 7

In this paper, a three layer neural network with back propagation learning algorithm is used as a network model for predicting the density of metal pipe material. The network is trained with a gradient descent technique. At the successful completion of the training, the root mean square (RMS) error is minimum for all of the training samples, and can be defined as follows:

$$E = \sqrt{\tfrac{1}{2}\sum (T_j - O_j)^2} = \min(E) \tag{4}$$

The simulation function based on the ANN was used as the objective function of the optimization problem, and the process window for each variable as given above was used as the boundary restrictions. The remaining 120 samples were then used to test and to train the performance of the ANN. As shown in Fig. 7,8.

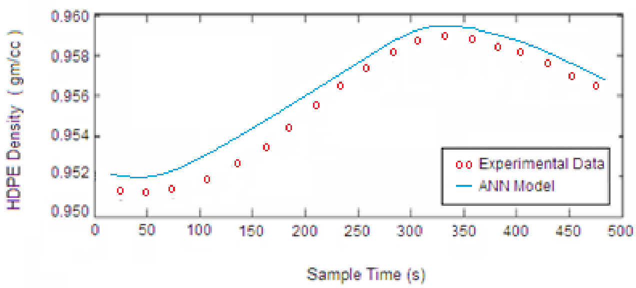

Figure 7. Plant and model responses to a unit step changes in test samples

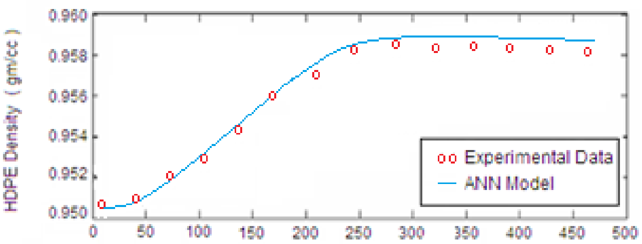

Figure 8. Plant and model responses to a unit step changes in train samples

A plot of neural network (NN) density predictions versus experimental density can be seen in Fig. 9.

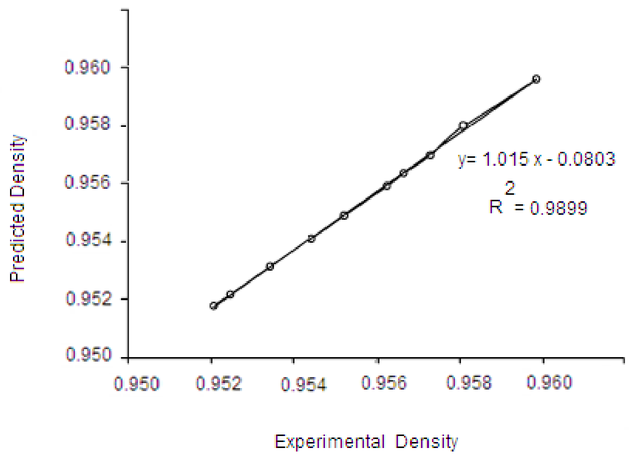

Figure 9. Comparison of experimental density and predicted density by ANN

Fig. 10 shows the experimental data and the predictions of the extrusion density by employing an ANN using HDPE pipe material. The process of extrusion was carried out with a sequence of eight extrudate velocities, 40, 45, 50, 55 and 60 rpm represented by 1 to 5, respectively.

The simulation was implemented with a 3-7-1 feed-forward network model. The three network input elements are the compositions of the materials pipe HDPE, the ratio of the die length and die diameter L/D = 12, the screw speed and the time t .

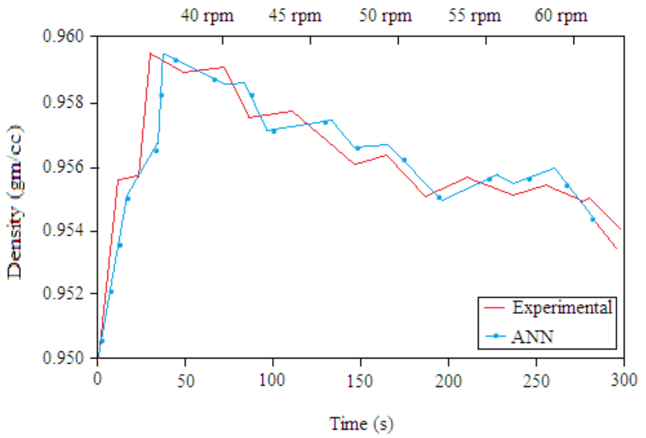

Figure 10. Experimental data and predictions of pipe extrusion by given ANN during extrusion in different screw speeds

4. Conclusion

In this study, experimental data and ANN predicted data studies are done to design an nonlinear comparison procedure for the density of pipe material HDPE during polymer extrusion process. Willing and setting density of 0.950-0.960 gm/cc in the range selected for the simulation of the system if it is predicted by ANN model. As a result, the artificial neural network (ANN), the desired pipe extruder system is predicted within acceptable limits.

Compared with values collecting from extruder piping process, values of ANN predicted observed that the ANN model, such as variable references under the system successfully. However, given the restrictions on the ANN model concluded that a more healthy work.

Back propagation model with three input, seven hidden and one output layer was used for the prediction of extrusion density. When compared with experimental data, this model shows that it is capable of predicting the mean extrusion density satisfactorily.

The ANN model is also a very useful tool to input and output parameters which are significant for the extrusion density. The existence or otherwise of water was found to have a most significant effect on the model output. The HDPE pipe material show a small effect on predictions of extrusion density.

5. Nomenclature

HDPE High Density Poly Ethylen
ANN Artificial Neural Network
η Learning Rate
μ Momentum Factor
θ_j Treshold Value
L layer L in ANN Model
n discrete time cycle number
x_i Output of the *i* th node in layer L-1
y_i Total weighted input in layer L
z_j Output of the *j* th node in layer L-1
d_j the difference between actual and predicted values
w_{ij} Weight representing the connection strength between the *i* th node *j* th node
T_j The target output of neuron j
Q_j The computed output from the neural network corresponding to that neuron
E Weight adjustment calculation to minimize the global error of the network

Acknowledgment

In this study, High Density Poly Ethylen (HDPE) pipe plastic material was used as test material. This work was supported by MARDİN PİPE CO. in Mardin, Turkey. The experimental value and data is given from this company.

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