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Article

Prediction of the Mechanical Behaviour of HDPE Pipes Using the Artificial Neural Network Technique

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Abstract. Actual statistics show that in recent years, more than 90% of the water distribution pipes installed in the world are made of plastic, exclusively polyethylene (PE). Due to the extensive use of these materials, it is necessary to have a good understanding of the mechanical properties of HDPE used for distribution system piping. For our study, we selected HDPE pipes as the material of choice. We then took a new approach to the analysis and prediction of mechanical properties, using new models based on Artificial Intelligence. In this paper, experimental tensile tests were conducted to obtain the mechanical properties of pipes. The first part of this work focuses on the mechanical tests, specifically tensile tests, while the second part centers on the numerical procedure for predicting the mechanical characteristics, a deep learning model was developed for prediction. The model was trained using a large dataset, including information on pipes. Specially designed deep learning architectures capture complex relationships and patterns in the data, enabling accurate predictions, Several ANN models were created to predict mechanical behaviour based on experimental data. We analyzed Bayesian regularization using MATLAB, an advantage of BR artificial neural networks is their ability to reveal potentially complex relationships. The results showed that the constructed prediction model is satisfactory since the M.S.E. value is nearly 0 (0.00023) and the R^2 value is close to 1 (0.99934). This study evaluates the advantages of our methodology by demonstrating the predictive power of an AI-based method and how well it predicts HDPE pipe behavior. The paper study will have significant effects on the water distribution and plastics industries.

Keywords: Prediction, HDPE piping, Matlab, mechanical property, artificial neural network, tensile tests.

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1. Introduction

Plastics have become one of the main materials used in various fields, among these materials we find polyethylene. Since the 1950s, extensive research has been devoted to analysing the characteristics of HDPE [1]–[5], This in-depth study has led to a better understanding of the material's mechanical, thermal, and chemical properties, as well as its behavior under various environmental conditions. In fact, polyethylene is recognised as one of the most adaptable and cost-effective materials in the plastics industry. In addition, it is recyclable and helps to reduce the impact of plastic waste on the environment [6]. Polyethylene is used in different sectors, more specifically we find the field of pipes for the manufacture of water and gas distribution pipes as well. Its versatility and excellent physical properties make it the material of choice for piping systems. Polyethylene pipe has excellent resistance to corrosion, abrasion, and chemicals, making it ideal for transporting liquids and gases in a variety of environments [7]. What's more, polyethylene is highly flexible, making it easy to install and reducing labor costs, and for that reason, polyethylene-based pipe replaced steel-based ones. High-density polyethylene (HDPE) pipes are increasingly being used in a variety of industrial and domestic applications [8] due to their superior mechanical and chemical resistance [9].

Predicting the mechanical behaviour of these pipes under various loading conditions is a challenging task that requires advanced simulation and modelling tools. In recent years, it has become clear that artificial neural networks (ANN) are powerful tools for the prediction of material properties [10]–[13]. ANN, on the other hand, are machine learning systems that can learn from data and provide very fast and accurate prediction models for the mechanical behaviour of HDPE pipes. To predict the mechanical behaviour of new HDPE pipes under various loading situations, ANNs can be trained using experimental data sets.

Technological advances have taken the study of materials to a new level, that of prediction. A large number of artificial intelligence (AI) tools are used to analyse and predict the behaviour of materials, and most of the time, ANNs are the most effective ones [14]. An ANN is a technique that can be used to predict the performance of plastic materials. Previous studies have proven that ANN is an effective tool. This work presents a new formulation for estimating the mechanical behaviour of HDPE (PE100) pipes using an ANN. These models were generated based on the results obtained during the experimental campaign. In addition, this dataset is integrated into the ANN model as input and target, and predictive analysis of the visits is performed. The performance of the predictive model is then tested. An ANN is described by a numerical structure similar to a biological network as shown in Fig. 1, which simulates basic features of the nervous system, such as learning, pattern classification, and data processing [15]. The model has been developed with easily obtainable prediction parameters. A brief description of the main features and functionalities of ANNs is presented, the methodology is described in detail, and the process of training ANNs and its use to generate the database for the development of the analytical formulation with non-linear regression is described.

ANNs are machine learning models used to perform classification, prediction, and function approximation tasks. MATLAB, an integrated development environment (IDE) widely used in engineering and science, also provides functionality for implementing and training ANNs. Using ANNs with MATLAB provides a complete environment for designing, training, and evaluating neural networks. MATLAB simplifies the development process and enables in-depth analysis of results thanks to its advanced features, several researchers and engineers are using this software to predict different parameters for different materials [16]–[21].

To the best of knowledge, no study has predicted the mechanical strength of HDPE pipes using ANNs based on experimental tests. On this topic, in the present work, we will investigate the optimal ANN model to predict the mechanical behaviour of HDPE pipes of PE100 grade from an experimental database. This paper explores the use of ANN models to predict the mechanical behaviour of HDPE pipes. The advantages and limitations of this technique will be discussed and their potential for improving the design and functionality of HDPE pipes will be highlighted.

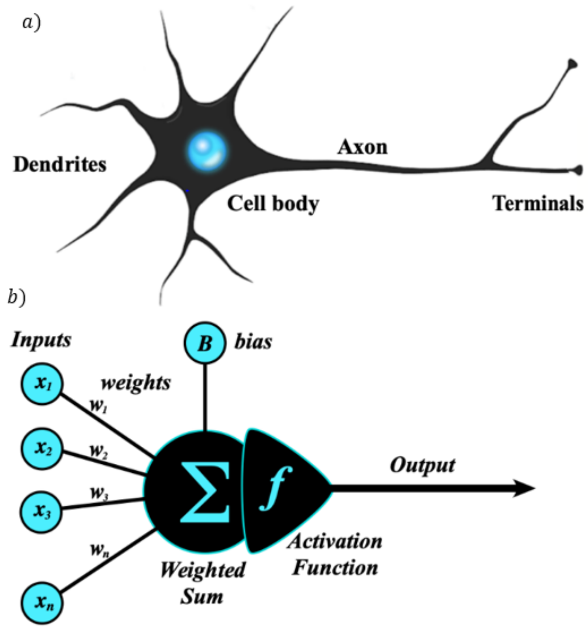

Fig 1. a) Biologic neurons; b) Artificial neurons.

The main contribution of this approach is to help operators in the drinking water network installation industry take the necessary precautions and reduce product losses within the industry.

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Table 1. Mechanical and thermal properties of HDPE.

Properties	Density	Fusion temperature	Crystallinity	Stress at failure	Elongation at fracture	Poisson ratio	Yong's module
Units	$g.cm^{-3}$	°C	%	MPa	%		MPa
HDPE	0.941 à 0.965	118 à 146	60 à 80	26 à 40	20 à 1000	0,40 à 0,45	600 - 1500
LDPE	0.915 à 0.935	105 à 115	<40	8 à 15	150 à 1000	0,42 à 0,48	200 - 300
MDPE	0.93 à0.945	125 à 128	40 à 60	18 à 28	200 à 1200	0,42 à 0,47	172 - 379

2. Materials

PE is defined as a linear polyolefin obtained by the radical polymerisation of ethylene, and the three main families of PE are defined essentially in terms of density: (i) low (LDPE), (ii) medium (MDPE), and (iii) high (HDPE). HDPE is a linear polyethylene with a density of 0.941 to 0.965 g/cm3 the details shown in Table 1. Over 90% of PE production is used in the four main applications of films, sheets, moulded products, and pipes. Amongst a wide range of applications, pipes are used in the agricultural irrigation and petrochemical industries to build networks for transporting pressurised liquids such as drinking water and natural gas. This data informs us of the development of PE as a potential alternative to metals and similar materials for special technical applications in the manufacture of spare parts, machinery parts, and coatings.

Figure 2 shows the HDPE pipes - class PE100. These high-density polyethylene resins are processed into pipes and assemblies to build natural gas and water transmission and distribution networks in Mediterranean, rural, and urban areas. According to statistics, most of the newly installed pipeline systems for gas and water supply in the world are made entirely of PE. The reasons for this choice are lightness, flexibility, price, ease of installation and maintenance, and resistance to aggressive substances. According to ASTM D 3350, plastic pipes (PE) can be classified according to their long-term performance, density, stress cracking resistance, melt index, flexural modulus, pigment stabilisers and ultraviolet stability. PE100 is more efficient than other PE grades, such as PE80 (PEMD), the latter being the most flexible and suitable for the manufacture of small-diameter pipes and other specific applications. Table 2 shows the properties of HDPE pipes-class PE100.

Fig. 2. Pipe of PEHD (PE100).

Table 2. Properties of HDPE pipe.

Properties	Density ($g.cm^{-3}$)	Yong's module (MPa)	Poisson ratio
values	959	1100	0.44

3. Specimen Preparation

The samples used in this study are taken from HDPE pipes with a blue stripe for drinking water supply, which are PE100 class with 40 mm outer diameter and 2 mm thickness. The shape of the sample was chosen in accordance with ISO 6259-3 [22], Fig. 3. The type of test specimen used illustrated in Fig. 4. To ensure that the molecular chains of the HDPE in the tube are oriented consistently in all formats, the orientation of the sample is the primary directional chain of the HDPE.

Fig. 3. Number of specimens studied.

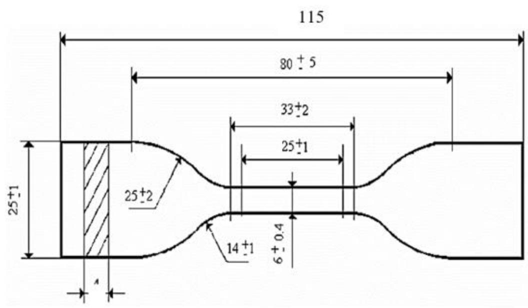

Fig. 4. Shape of the HDPE-PE100 pipe specimens.

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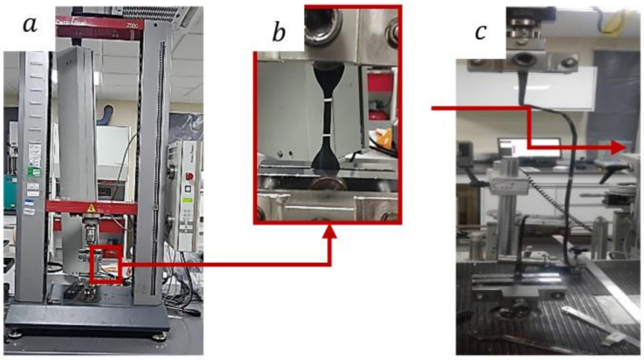

Fig. 5. Tensile test of the specimens of HDPE-PE100 pipes—a) Test start; b) Extension; c) fracture.

4. Experimental Procedure

Tensile testing is a mechanical procedure for determining the tensile strength of materials [17], [23]–[25]. It involves subjecting a material sample to a tensile force until it breaks. To determine the tensile strength, yield strength, strain resistance, and ductility of the material, data collected during the experiment can be used. The standard method for performing a tensile test on HDPE pipes is ISO 6259-3 [22], which specifies the test conditions, the equipment required, and the procedures for performing the test.

The experimental tensile test platform includes a test set-up involving a ZWICK/ROELL Z020 Instrument, 40 samples of HDPE pipes, equipment for attaching the sample to the tensile test set-up, and a data acquisition system for recording the test results, a CTPC mechanical laboratory.

The samples of HDPE pipe are typically cut at 25 mm as given in Table 3. Then, as shown in Fig. 5, it is fixed to the traction-testing device's two ends and put under traction pressure until it breaks. To determine mechanical characteristics such as the traction resistance, elastic limit, and ductility of the PEHD tube, the data gathered throughout the experiment may be used.

Table 3. Dimensions of the HDPE-PE100 pipe specimens.

Description	Dimensions (mm)
Total length	115
Width at extremities	25+-1
Length of narrow part, with parallel sides	33+-2
Width of the narrow part, with parallel sides	6+-0.4
Small bending radius	14+-1
Large radius of curvature	25+-1
Length between reference marks	25+-1
Initial distance between the clamps	80+-5
Thickness	Its specimen dependence

5. Numerical Procedure

5.1. ANN Technique

Since its creation, artificial intelligence (AI) has demonstrated that it can be applicable to a wide range of sectors not necessarily related to computing. Among the most important usages are medicine [26], security [27], [28], education [29], Photovoltaic [30] and materials science [31], [21], [32]. Modern machine learning algorithms, such as ANNs, have been successfully used in numerous system modeling fields in recent years [33]–[36]. ANN is a mathematical model that is based on the biological organisation of neurons and the architecture of the brain. In a multi-layer neural network, the perceptron (the basic unit that constitutes an ANN) is structured hierarchically in layers. A layer is a set of unconnected neurons that receive input from the same source (external or other layers) and send their information to the same destination (other layer or external) as shown in Fig. 6. Therefore, we can distinguish between three types of layers [37]. Input layers that receive data from outside, a hidden layer is a layer whose inputs and outputs are inside the system and thus have no contact with the outside world. Finally, an output layer sends the network's response.

In the field of materials science, various artificial intelligence techniques have been developed to perform various types of analysis or prediction of the characteristics and behavior of industrial components and materials [38]–[44].

In this article, we developed an ANN architecture specifically designed to solve our problem. The aim is to use the machine learning capabilities of ANNs to predict the tensile strength of HDPE pipes by analyzing the dataset. The ANN architecture developed has been optimized using Matlab as the software utility. Because the dataset is small, a single hidden layered ANN design has been implemented for this study, making it computationally less difficult and easier to train. In other words, a single hidden layer simplifies the network, activation functions induce nonlinearity, and an effective training method is required for changing weights to reduce mistakes during training. A few investigations have shown that a single hidden layer can capture the required patterns and connections in data in various scenarios [45].

The choice of activation functions affects the network's capacity to simulate complicated, nonlinear interactions. The tan sigmoidal and purelin functions have been utilized in the current investigation for the hidden and output layers, respectively. In the current study, the dataset is divided into 70% training and 30% testing subsets. Even if the dataset is limited in scope, the quality and relevancy of the data are crucial. Preprocessing data ensured that the model could learn meaningful patterns from the supplied data, resulting in improved generalization and performance [46].

Figure 6 shows the ANN architecture developed for this study. The Bayesian regularization-based (BR) model is trained using experimental data during the initial training step. After the model training was completed, 30% of the data was utilized to validate the trained model during the testing step. As illustrated in Fig. 6, the network is divided into three layers: input, hidden, and output. Figure 6 depicts the proposed neural network design with 'tansig' and 'purelin' functions, The "tansig" function is used to introduce non-linearity and model complex relationships between input and output variables, the function is shown in Eq. (1) [47]. In addition, the "purelin" function is used for linear prediction where the output is a continuous estimate without nonlinear transformation, the function is shown in Eq. (2) [47]. The experimental data was utilized to choose the variables needed for the computational investigation, which were later used for ann modeling. Tensile strength is predicted using the suggested ANN model. Using experimental data, elements such as strain speed, density, thickness, width, and force were examined as inputs for model building.

$$\mathrm{tansig(n)} = \frac{2}{1+e^{-2n}} - 1 \tag{1}$$

$$\mathrm{purelin(n)} = \mathrm{n} \tag{2}$$

where n is the function input.

The developed ANN model was trained using the Bayesian regularization backpropagation technique; Bayesian regularization (BR) is a powerful technique with a lower mean square error than other algorithms for function approximation problems. The Bayesian framework for neural networks is based on the probabilistic interpretation of network parameters [48]–[50], the model was verified and evaluated using experimental data samples later.

The algorithm with the highest coefficient of determination (R^2) and the lowest mean square error (MSE) value was selected as the best algorithm. For the five input parameters and one output parameter considered in the study, the R^2 and MSE values were determined using the following mathematical Eq. (3) and Eq. (4) [51]:

$$R^2 = 1 - \sum_{i=1}^{m} \frac{(y_p^i - y_a^i)^2}{(y_{avg,\ a}^i - y_a^i)^2} \tag{3}$$

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_p^i - y_a^i)^2 \tag{4}$$

where "y_a" represent the actual value, "y_p" represents the predicted value, "$y_{avg,a}$ " represents the average of actual value, and "m" represents the total number of samples.

6. Results and Discussion

6.1. Experimental Results

In this study, the results of tensile testing of 40 HDPE pipe samples are presented, followed by the results of mechanical property prediction using ANN techniques. Tensile tests provide valuable information about the mechanical properties of the material under investigation. The variability of the results highlights the importance of taking into account the variability of mechanical properties when designing and using such materials in practical applications.

Tensile strength at yield for the HDPE pipes is one of the most widely used parameters for comparing the strength of different materials and is measured in tensile tests. It gives the force required to bring the sample to failure as shown in Table 4. However, the mode of rupture of plastics is very different from that of metals.

The experimental work is carried out as shown in Fig. 5. Table 4 presents a typical set of data from the experimental results. The variables included in this table have an important impact on the HDPE pipes grade PE100's tensile strength. Sample size, temperature, and stress loading rate are the order of the process parameters that affect the tensile strength.

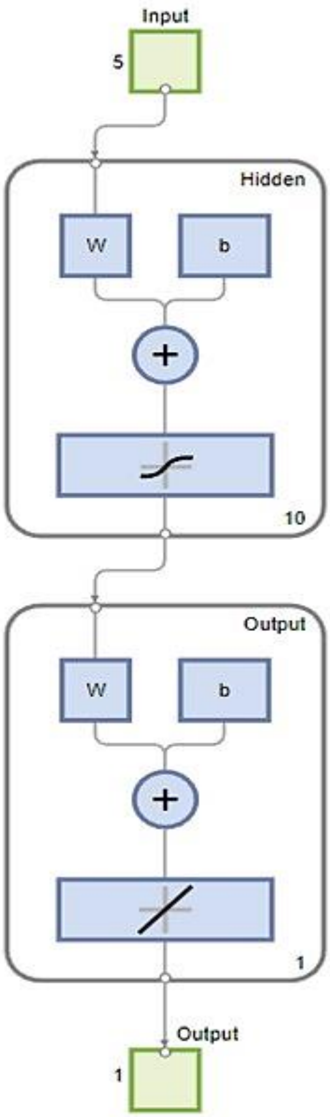

Fig. 6. ANN architecture of the proposed model.

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Table 4. Result of experimentally measured tensile strength.

Samples	The strain speed mm/min	Density kg/m^3	Thickness (mm)	Width (mm)	Tensile strength (MPa)	Force (N)
1	100	959	2.37	5.70	27.6	365.000
2	100	959	2.15	5.75	29.0	358.773
3	100	959	2.18	5.67	36.8	453.860
4	100	959	2.35	5.70	32.5	435.067
5	100	959	2.30	5.77	26.9	356.959
6	100	959	2.34	5.66	27.7	366.591
7	100	959	2.40	5.72	34.3	470.426
8	100	959	2.33	5.74	33.7	449.976
9	100	959	2.39	5.74	29.8	406.964
10	100	959	2.30	5.74	24.6	324.964
11	100	959	2.14	5.76	37.9	466.831
12	100	959	2.23	5.67	36.4	459.079
13	100	959	2.09	5.70	38.2	454.330
14	100	959	2.18	5.66	35.0	430.548
15	100	959	2.24	5.60	32.1	402.280
16	100	959	2.25	5.60	39.0	484.140
17	100	959	2.15	5.70	32.9	401.785
18	100	959	2.15	5.64	31.5	381.665
19	100	959	2.08	5.73	35.9	428.173
20	100	959	2.36	5.68	22.7	264.701
21	100	959	2.20	5.60	33.6	413.660
22	100	959	2.05	5.65	39.4	456.441
23	100	959	2.35	5.64	28.8	381.731
24	100	959	2.30	5.60	27.2	350.197
25	100	959	2.15	5.66	39.3	477.617
26	100	959	2.17	5.66	32.8	402.577
27	100	959	2.40	5.62	36.9	497.408
28	100	959	2.08	5.65	39.0	458.519
29	100	959	2.27	5.59	39.8	505.126
30	100	959	2.30	5.60	37.1	476.660
31	100	959	2.03	5.55	33.8	380.279
32	100	959	2.38	5.49	30.1	392.714
33	100	959	2.30	5.70	29.3	384.138
34	100	959	2.08	5.72	32.6	387.470
35	100	959	2.40	5.70	35.6	487.578
36	100	959	2.19	5.54	35.4	428.239
37	100	959	2.24	5.60	36.8	461.949
38	100	959	2.25	5.65	30.0	381.500
39	100	959	2.38	5.63	35.5	474.120
40	100	959	2.35	5.61	35.1	462.246

Tensile tests on HDPE pipes show solid tensile strength, confirming the excellent mechanical properties of this material. It can be said that HDPE pipes have a higher tensile strength than other types of pipes, due to their linear molecular structure and high density. Test results have shown that HDPE pipes are capable of withstanding considerable loads without permanent deformation or breakage. This superior tensile strength enables HDPE pipes to be used in applications requiring high reliability and robustness, such as drinking water pipelines. The tensile test results confirm that HDPE pipes have good tensile strength, making these pipes ideal for many applications requiring reliable mechanical properties.

6.2. Prediction Results

In this section of this paper, we put the previously proposed algorithms into practice by applying them to experimental data in Table 4 to predict the tensile strength of HDPE pipes.

The prediction results highlight the model's performance and allow an in-depth assessment of its accuracy. Figure 7 depicts a summary of Regression graphs throughout the training, testing, and validation stages of the ANN model training process. An overall R^2 score of 0.99934 was found for the training data samples. The total R^2 value is close to 1.0, indicating that the results are good. Notably, the R^2 value at each step is near 1.0, as shown in Fig. 7, with values of 0.99962, 0.99965, and 0.99801 for training, validation, and testing, respectively. Table 5 illustrates the model performance during the training of the ANN model.

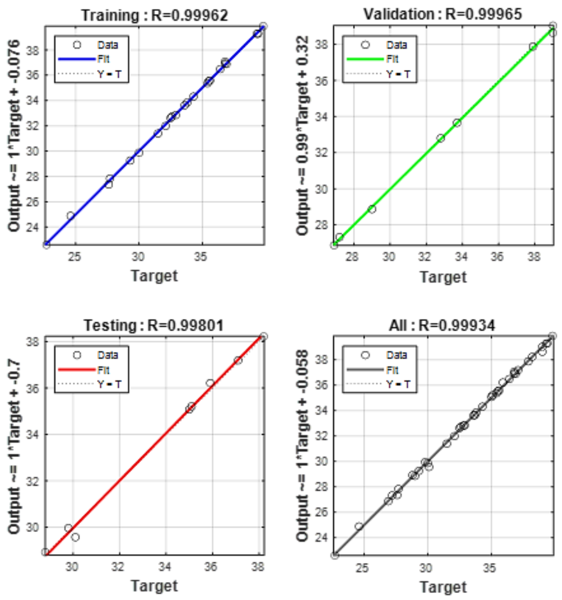

Fig. 7. Regression plots during the training process.

Figure 8 is an error distribution figure that depicts the error values, which are the differences between the desired and anticipated values, which means that [error = targets – outputs]; the plot created displays an error histogram. After ANN training, the errors are measured on the horizontal axis, whilst the instances, i.e., sample values from the dataset, are quantified on the vertical axis. A line with dots denotes zero error.

Table 5. Model training performance values.

Epoch	0	78	999
Elapsed Time	-	0:00:01	-
Performance	6.44	0.00023	0
Gradient	11.7	1.72E-04	1.00E-07
Mu	0.005	5.00E+10	1.00E+10
Effective # Param	51	13.6	0
Sum Squared Param	131	3.89	0

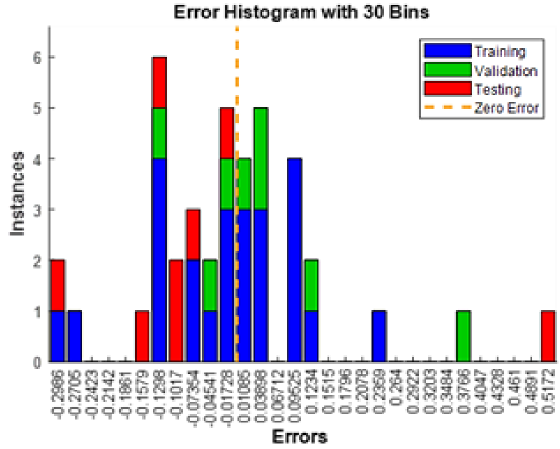

Fig. 8. Error histogram plot.

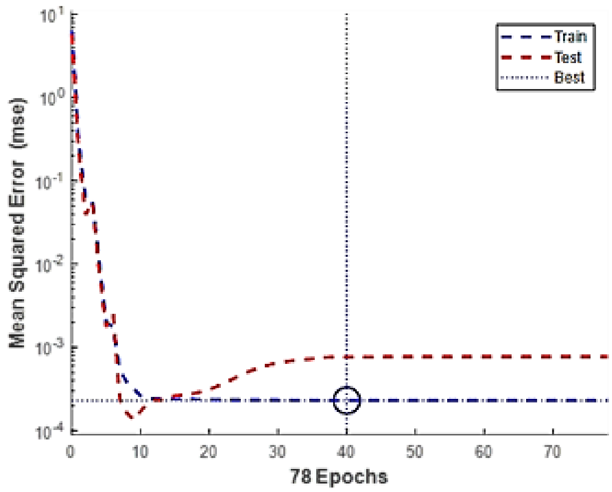

Fig. 9. ANN model best performance plot.

Figure 9 depicts a relationship between Mean Squared Error (MSE) and Epochs. At epoch 40, the validation plot achieved the best validation performance, with a minimal MSE value of 0.00023. Furthermore, unused sample data samples were chosen from experimental data for prediction. The strain speed, density, thickness, breadth, and force data were afterward used as inputs by the constructed ANN model to estimate tensile strength. Figure 10 depicts the plot of the actual tensile strength vs the tensile strength values. As demonstrated visually in Fig. 10, the plot reveals reasonable agreement between actual and anticipated data values.

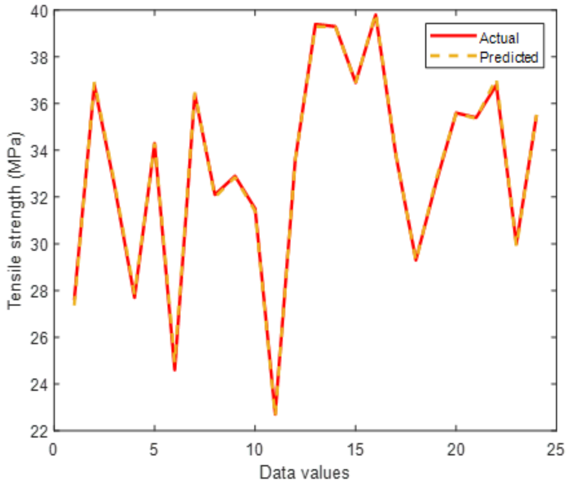

Fig. 10. Experimental values vs predicted value.

7. Conclusion

In summary, this paper explores the use of ANNs to predict the mechanical properties of high-density polyethylene (HDPE) pipes. The results obtained show that ANNs can be an effective technique for predicting the mechanical properties of HDPE pipes. In the present study, predictions of the mechanical properties of HDPE pipes are made. The Following conclusions were obtained:

- The tensile strength modeling of HDPE pipes obtained with a trained ANN closely matches the experimental results, making neural networks a very favorable model for predicting the mechanical behavior of plastic pipes. Artificial intelligence methods can be used to correctly predict the mechanical behavior of plastic pipes. Unlike the usual modeling methods, the discovered model does not require exact equations.
- It should be noted that the results obtained depend on the quality of the input data and the proper design of the neural network. Therefore, further research is needed to improve the performance of ANNs in predicting the mechanical properties of HDPE pipes, optimizing network parameters, and expanding training datasets.
- Future perspectives for this study include improving the performance of ANNs by using more advanced architectures and exploring more sophisticated learning techniques. The integration of additional data such as specific manufacturing conditions, environmental data, and material properties could improve the accuracy of predictions.

Applying the appropriate machine learning algorithm model not only improves the accuracy of product quality prediction but also reduces development time and costs.

Future research could develop a more accurate prediction model by including significant input characteristics, and then assess the differences between artificial intelligence-based models and standard methods. The lifetime of pipes can be predicted over time with the use of predictions about the mechanical behavior of HDPE pipes.

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