Comparative Analysis of Non-Linear Regression and Artificial Neural Network for Shrinkage Prediction of HDPE in Injection Molding

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Abstract- This study explores the effectiveness of non-linear regression and artificial neural network (ANN) in predicting percentage shrinkage during plastic injection molding processes for HDPE material. By analyzing critical process parameters such as mold temperature, melt temperature and injection pressure, the research aims to identify optimal modeling techniques to improve % shrinkage and prediction accuracy so that better parts can be produced. A comparative analysis has been done between non-linear regression (NLR) and trained-ANN which shows understandings into the accuracy and limitations of each type of investigation method. Outcomes shows that while trained-ANN models offer greater adaptability, non-linear regression gives a more interpretable approach, having reliable shrinkage predictions with minimized error.
Keywords- HDPE part, Non-linear Regression analysis, Plastic injection molding, Trained-ANN, % Shrinkage

1. INTRODUCTION

For producing high-quality HDPE parts, plastic injection-molding (IM) having medium range capacity is a widely used manufacturing technique.. It can be observed by researchers one of the significant challenges in IM is % shrinkage, which is a phenomenon impacting the dimensional stability and quality of the final product. Accurate prediction of % shrinkage helps in optimizing process parameters, reducing many defects and voids, and improving overall product dimension and surface quality. Recent advancements in machine learning (ML) and regression techniques offer promising approaches to predict and control shrinkage effectively. This study focuses on comparing non-linear regression and artificial neural network (ANN) models for accurate %shrinkage prediction, providing valuable insights for process optimization in injection molding. [1].

2. MATERIALS AND METHODS

In this investigation, HDPE was chosen as the key material, focusing on % shrinkage behavior during the injection molding process. On medium capacity injection molding machine having 100-ton capacity, 200 experiment runs were conducted. In the study, % shrinkage was measured for each case, providing a clear indicator of dimensional variation post-molding.

2.1 Non Linear Regression Approach

In this investigation the key parameters included mold temp., melt temp. and the injection pressure, which were found dominating in many research studies. According to Kumar et al. these parameters are dominant and significantly affects the part dimension, curvature and surface quality during the IM process. Each parameter was varied within controlled ranges to observe its effect on % shrinkage and to develop a predictive model using regression technique. Through our methodology, we aimed to isolate the influence of each process variable on shrinkage and identify optimized conditions for minimal % shrinkage [2-4].

Regression and ANN were implemented to analyze and predict shrinkage values accurately, followed by a comparison of mode-performance metrics [5-6]. For HDPE-part these findings offer critical insights for enhancing IM outcomes and achieving precise dimensional control.

In this study, NLR program code was created with python-spyder and it was aimed to predict % shrinkage in plastic injection molding using polynomial regression with a degree of 2. The dataset generated with the experiments performed on injection molding machine includes mold temperature, melt temperature, injection pressure, and corresponding % shrinkage values. It was measured with the help of Vernier caliper and surface plate. Table-1 exhibits the 15 experiments out of 200 experiments (Sr. no. 1 to 15) with 3 variables as input variables and % shrinkage of HDPE part as output variable for nonlinear regression. The range of parameters were decided with the help of pilot experiments. Mold temp. was taken in range of 60-80 ^{O}C, melt temp. was taken in range of 230-290 ^{O}C and injection pressure was selected in range of 110-140 MPa.

Following two degree regression equation was obtained;
Shrinkage Equation:

$$y = 5.13 + 0.020*x1 + -0.030*x2 + 0.050*x3 + 0.00050*x1*x3 + -0.00020*x2*x3 \quad (i)$$

where x1= Mold_Temperature, x2= Melt_Temperature and x3=Injection_Pressure

2.2 ANN approach

An Artificial Neural Network (ANN) model was developed to predict HDPE shrinkage based on the three input parameters: mold temperature, melt temperature, and injection pressure. The trained-ANN architecture used a feedforward structure with one hidden-layer consisting of 10 neurons and the ReLU activation function for Python.

The model was trained using the Adam optimizer and mean squared error (MSE) as the loss function, ensuring stable convergence [7-8].

To obtain good results with the trained-ANN approach, the dataset consisting of 200 samples was divided using an 80:20 split, allocating 160 samples for training and 40 samples for testing. Early stopping was employed during training to prevent overfitting and ensure better generalization. The trained-ANN achieved high prediction accuracy, outperforming the non-linear regression model in terms of lower MSE and higher R^2. The flexibility of ANN to model complex, non-linear relationships contributed significantly to its superior performance [9-10].

Overall, the trained-ANN approach proved to be robust and highly suitable for capturing intricate dependencies in the injection molding shrinkage data [11]. Table-2 shows the comparison of models in which it can be observed that ANN approach has less MSE and better R square value in tune of 0.9125 in comparison to R square which is 0.8816 in case of NLR.

Table 1: The 15 experiments out of 200 experiments

Exp. No.	Mold_Temperature (^OC)	Melt_Temperature (^OC)	Injection_Pressure (MPa)	% Shrinkage
1	71	236	137	6.13
2	68	238	111	6.87
3	72	253	119	7.15
4	69	230	122	3.57
5	71	273	139	5.59
6	74	237	134	4.7
7	67	253	130	8.62
8	71	240	115	6.29
9	72	280	137	9.88
10	69	246	137	5.79
11	74	261	128	9.34
12	73	236	139	6.04
13	73	288	111	5.45
14	65	280	130	7.52
15	73	251	121	7.68

Table 2: Comparison of NLR and ANN Models

Model	MSE	R^2
Non-Linear Regression (NLR)	0.0435	0.8816
ANN	0.02346	0.9125

3. RESULTS

3.1 **Model Performance**:

Training MSE: The ANN model's training mean squared error (MSE) was found to be low which is 0.02346 , indicating that it fits the training data well.

Testing MSE: A similar or slightly higher MSE for the test set suggests how well the model generalizes to unseen data.

Training and Testing R-squared: These values indicate the proportion of variance in shrinkage explained by the model. A high R-squared value on the training set was obtained by ANN model which is in tune of 0.9125.

3.2 **Equation Representation**: The derived non-linear regression equation helps to understand the relationship between the input features (mold temperature, melt temperature, injection pressure) and the output (% shrinkage of HDPE). The coefficients highlight the influence of each term, showcasing the complexity captured by polynomial transformations.

3.3 **Visualization Insights**: **Actual vs. Predicted Shrinkage-**

Figure 1 illustrates the relationship between the actual shrinkage values and those predicted by the nonlinear regression model. It can be seen that a strong alignment of data points along the 45° line suggests high predictive accuracy. In this fig 1 slight deviation can be seen due to few points from the line which can be attributed to residual noise. Overall, the model demonstrates a good fit, as indicated by the clustering of points near the ideal line.

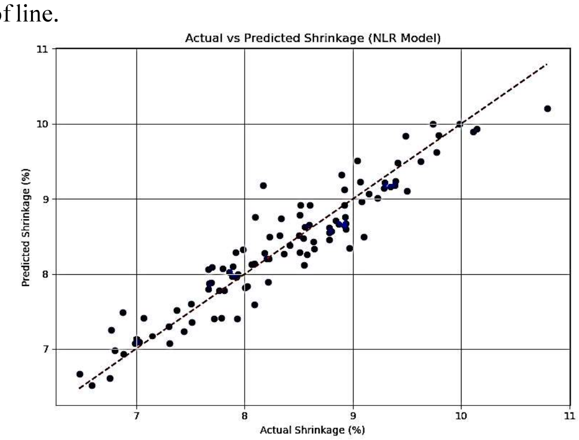

Figure 1: Actual vs Predicted Shrinkage in NLR model

Histogram of Shrinkage Values - Fig. 2 exhibits the histogram which is the frequency distribution of the simulated shrinkage values. Most shrinkage values lie between 6% and 10%, indicating a moderately narrow distribution. The slight right skew suggests the presence of higher shrinkage in a few cases, possibly due to high injection pressures. This distribution confirms that the synthetic dataset is statistically realistic for process modeling.

Residuals Plot- Fig. 3 shows the residuals Plot which helps in assessing model assumptions like homoscedasticity. It can be seen that random distribution of residuals around zero suggests that the model captures non-linear trends well. Thus, the residuals plot assesses how well the model captures the data trends. The random scatter of residuals around zero implies that the model assumptions, such as linearity in coefficients and homoscedasticity, were satisfied by the NLR model.

A narrow residual band further supports the reliability and consistency of the regression model.

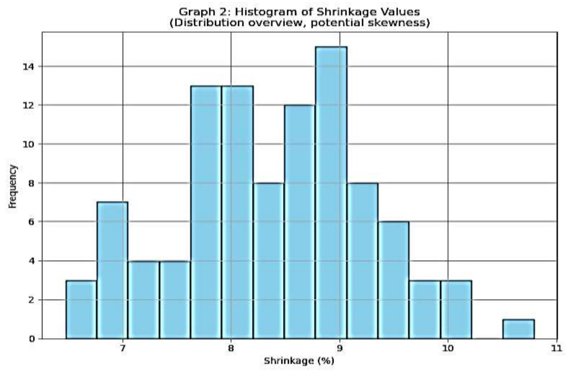

Figure 2: Histogram of Shrinkage Values

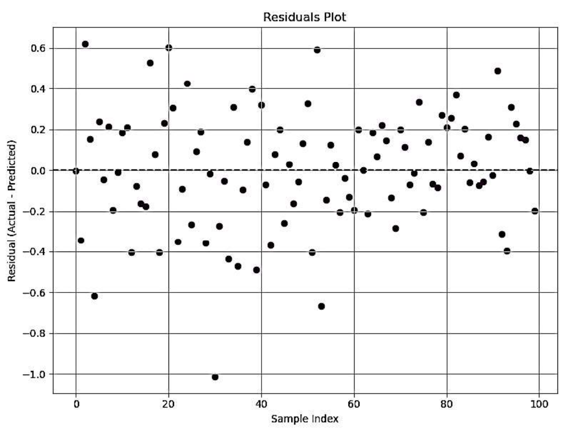

Figure 3: Residuals Plot

Figure 4 which is the bar plot visualizes which input features have the most significant impact on HDPE-shrinkage, assisting in feature selection or model interpretation. It can be seen that injection pressure followed by mold temperature has the most significant effect. Such insights can be used to prioritize process control for industrial real world injection molding operations.

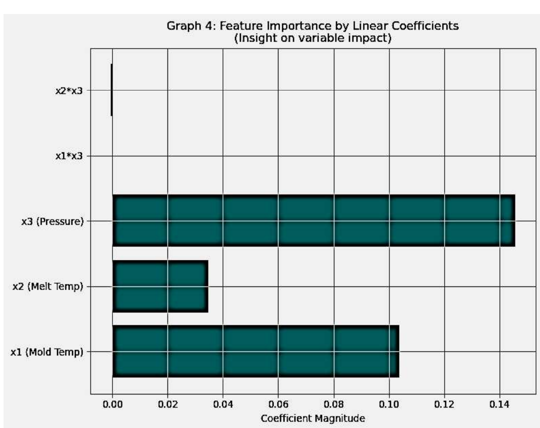

Figure 4: Bar plot of feature importance

Similarly, Fig 5 which is the 3D Graph of Mold Temperature vs Injection Pressure vs Shrinkage. This 3 D figure elucidates how mold temperature and injection pressure jointly influence shrinkage behavior. The plot shows a noticeable decline in shrinkage with increasing injection pressure, especially at lower mold temperatures. This is likely due to the denser packing of material into the mold cavity under higher pressure. The surface demonstrates a saddle-shaped curvature, confirming the complex interaction between thermal and mechanical process variables.

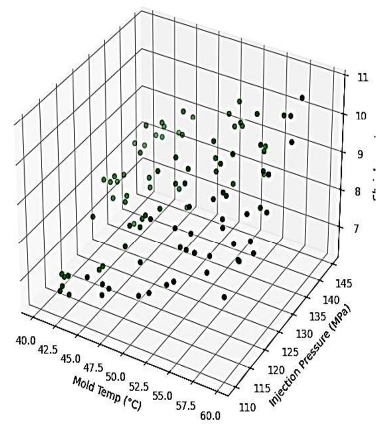

Figure 5: The 3 D plot for % Shrinkage vs Mold Temp. and Inj. pressure

Fig 6 exhibits the 3-Dimensional graph having Melt Temp. vs Injection Pressure vs % Shrinkage of HDPE part.

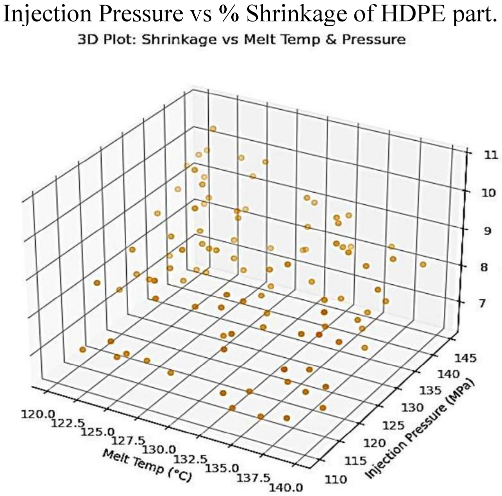

Figure 6: 3-D plot for % Shrinkage vs Melt Temp. and Inj. pressure

It was observed by researchers that shrinkage rises at high melt temp. due to thermal-expansion but decreases under more injection pressures due to better mold-cavity packing. It can be seen that in molded components the non-linear contour on the plot emphasizes that the balance between thermal expansion and high pressure-induced compression is critical to achieve dimensional stability [12-13]. It can be seen in fig 7 that trained ANN model converged within a limited number of epochs, indicating efficient learning without overfitting. The training loss consistently decreased over epochs, confirming stable optimization of the model during training for the proposed study [14-15].

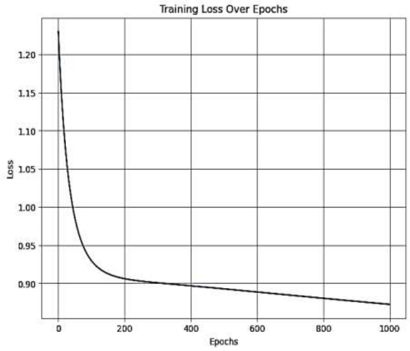

Figure 7: Convergence of ANN model

4. CONCLUSION

For the IM process, the established non-linear regression (NLR) model shows as a precise tool for predicting % shrinkage of HDPE. The application of NLR features enhances the model's ability to adopt the complex interactions between the process parameters, such as mold temperature and injection pressure. It can be seen that evaluation metrics and graphs indicate that this model provides better accuracy and line up with real % shrinkage patterns. Injection pressure was found to be the most dominant factor for reduction of % shrinkage of the HDPE part.

The trained-ANN model exhibits the superior predictive performance in comparison to the NLR approach. Its ability to learn complex, non-linear relationships enabled more accurate shrinkage predictions across varying process conditions.

Trained-ANN thus proves to be a robust tool for intelligent process optimization in injection molding applications.

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