Optimisation Of Injection Moulded High Density Polyethylene-Sawdust Composite (Percentage Elongatıon And Average Deflection)

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Abstract- The focus of this study is on the modeling and optimisation of percentage elongation and average deflection using injection moulded high density polyethylene-Sawdust composite. The HDPE material and sawdust were mixed together to form a homogenous mixture with various percentage composition by volume as obtained by the central composite design (CCD). The response surface methodology (RSM) and artificial neural networks (ANN) were used to determine the effect of the interaction of temperature and percentage by volume of material on the mechanical properties of the produced HDPE-sawdust composite. Models were developed for predicting the mechanical properties percentage elongation and average deflection) for the produced composites. The models were validated using coefficient of determination (R2). The coefficient of determination (R2) obtained ranged from 0.9213 (92.13%) to 0.981 (98.10%) which indicates a good fit was achieved between the model and experimental results. The optimization results for HDPE-Sawdust composites shows that the percentage elongation and average deflection were minmized with values of 90.98% and 2.46cm obtained at barrel temperature of 164.64 ^{o}C and polymer level of 68.54%.

Keywords- Central composite design Composite Modeling High density polyethylene Sawdust percentage elongation.

Özet - Bu çalışmanın odak noktası, enjeksiyonla kalıplanmış yüksek yoğunluklu polietilen-Talaş kompozit kullanılarak yüzde uzama ve ortalama sapmanın modellenmesi ve optimizasyonu üzerinedir. HDPE malzemesi ve talaş, merkezi kompozit tasarım (CCD) ile elde edildiği gibi hacimce çeşitli yüzde bileşimleriyle homojen bir karışım oluşturmak için birlikte karıştırıldı. Yanıt yüzey metodolojisi (RSM) ve yapay sinir ağları (YSA), üretilen HDPE-talaş kompozitinin mekanik özellikleri üzerindeki malzeme hacmi ile sıcaklık ve yüzde etkileşiminin etkisini belirlemek için kullanıldı. Üretilen kompozitler için mekanik özellikleri yüzde uzama ve ortalama sapma) tahmin etmek için modeller geliştirilmiştir. Modeller, belirleme katsayısı (R2) kullanılarak doğrulanmıştır. Elde edilen belirleme katsayısı (R2) 0,9213 (% 92,13) ile 0,981 (% 98,10) arasında değişmekte olup, bu da model ile deneysel sonuçlar arasında iyi bir uyum sağlandığını göstermektedir. HDPE-Talaş kompozitleri için optimizasyon sonuçları, 164,64 oC namlu sıcaklığında ve% 68,54 polimer seviyesinde elde edilen yüzde uzama ve ortalama sapmanın% 90,98 ve 2,46 cm değerleri ile minimuma indirildiğini göstermektedir.

Anahtar Kelimeler- Merkezi kompozit tasarım Kompozit Modelleme Yüksek yoğunluklu polietilen Talaş yüzdesi uzaması.

1. Introduction

The demand for new materials with higher specifications has led to the concept of combining different materials to form a single material called composite. Such composite materials result in high performance, and high flexibility in design that cannot be attained by the individual constituents. Moreover, it has been shown that technological development depends on the progress in the field of material sciences [1].

The mechanical properties of composite panels wet to depend on the density variations that occur through the pan thickness. They then proposed an analytical tool to predict density profile as a function of the manufacturing processes. A multilayer description of the density and moisture gradients resulting from the felting process provided input for the mode Inputs for the pressing process included plate temperature and press closing rate. The model they developed simulated the physical and mechanical processes that occur in the press and mat system [2].

The modeling and optimization of some mechanical properties of injection moulded HDPE sawdust composite, some of the properties they worked on includes tensile strength, proof stress, flexural strength and flexural modulus were examined and optimized [3], however our focus in this study is percentage elongation and average deflection of HDPE sawdust composite.

2. Materials and Methods

2.1 Material

The following materials were used for this work:

High density polyethylene (HDPE) in powder form was used for this study. Sawdust (from Mahogany tree) Based on it's was readily availability and mechanical properties desired). Two stage-screw plunger Injection machine Fox and offord, 120 tons two stage-screw plunger, A toggle clamp attached to the injection end of injection moulding. MONSANTO TENSOMETER, Type 'W' Serial No. 8991, The mould was made of Silicon – killed forging quality steel AISI type H140 treated to 252 –302 Brine 11. Such steel was used for moulds that require high quality parts, long production runs and is s safe to use at high clamping pressures. The following are the dimension of the mould used:

2.2 Modelling

2.2.1 Design of Experiment

For this study, a two-variable central composite design (CCD) was used to plan the experiments, develop statistical models for predicting the chosen responses and to optimise the responses and factors. The CCD is a very versatile experimental design method. The design points are made up of 2n factorial points as well as star points. The star points are particularly necessary for estimating the curvature of the response surface especially for nonlinear models. The CCD is the only response surface design that can be used for planning experiments with two factors [4].

2.2.2 Modelling using Response Surface Methodology (RSM)

Response surface methodology RSM is a practical mathematical and statistical tool that can be employed for analyzing the effects of several independent factors on the treatment process in order to obtain the maximum benefit from the process. Recently, several water and wastewater treatment processes have been optimized for treatment different type of wastewaters via RSM including; textile dye wastewater, tannery wastewater, industrial paint wastewater, landfill leachate, olive oil wastewater, and palm oil mill effluent [5].

2.2.3 Determination of Optimal Training Algorithm

It is not usually possible to determine beforehand, the best algorithm to use for training a proposed neural network. Thus, it is usually necessary to iteratively test several training algorithms to determine the one most suitable for a particular network [6]. The same thing applies to the network architecture. Hence, in this work, two networks architectures were considered and trained using different training algorithms to determine the one that will be most suitable to model the responses. The network architectures evaluated were the multilayer normal feed forward (MNFF) and multilayer full feed forward (MFFF) while the training algorithms evaluated were incremental back propagation (IBP), batch back propagation (BBP), quick propagation (QP), generic algorithm (GA), and Levenberg-Marquardt (LM) algorithm. The results showed that the best network was a multilayer normal feed forward neural network trained with the incremental back propagation algorithm. This was found to be suitable for predicting all the responses. The decision to select this network architecture and training algorithm was because it resulted in the highest R^2 value and lowest RMSE value for the responses under consideration.

2,2,4 RSM and ANN Data Verification

The predictive capability RSM and ANN was evaluated by comparing the results predicted by the RSM and ANN models with the experimental data. The extent of fit between the experimental and model predicted results was evaluated using some statistical tools such as the coefficient of determination (R^2 value), root mean square error (RMSE), and absolute average deviation (AAD). These terms are defined as shown in Equations (1) to (3) [7].

$$R^2 = 1 - \sum_{i=1}^{n} \left(\frac{\left(y_{\exp} - y_{pred}\right)^2}{\left(y_{\exp} - y_{\exp,ave}\right)^2} \right) \quad (1)$$

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} \left(y_{pred} - y_{exp} \right)^2 \right)^{1/2} \quad (2)$$

$$AAD(\%) = \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_{\exp} - y_{pred}}{y_{\exp}} \right) \right) \times 100 \quad (3)$$

Where, n is the number of points

y_{pred} is the predicted value obtained from the model

y_{exp} is the actual value

$y_{ave,exp}$ is the average of the actual values.

The coefficient of determination is used as a measure of the degree of fit between the model results and the experimental results [8]. Generally, the closer the R^2 value is to 1, the better the level of fit between the experimental results and model predictions [9]. RMSE and AAD are statistical parameters for expressing the deviation between the experimental results and the model predictions. Generally, it is desired that the RMSE and AAD between predicted and experimental results be as small as possible [10].

4 3. RESULTS AND DISCUSSION

3.1. Determination of Appropriate Model

As alluded to in the previous chapter, different statistical models were examined with the intention of selecting the one most appropriate to represent the process under consideration. Amongst the models examined were the linear, two-factor interaction (2FI), quadratic and cubic models. Table 1 shows the results of this exercise. The decision to choose or discard a model was taken based on the values of statistical parameters like standard deviation, coefficient of determination (R^2 value), p value, F value etc.

Table 1: Summary of model fit results (HDPE-Sawdust composite)

Percentage elongation								
Source	Standard deviation	R^2	Adjusted R^2	Predicted R^2	PRESS	F-value	p-value	Remark
Linear	3.91	0.8542	0.8251	0.7235	289.46	18.31	0.0071	

2FI	4.12	0.8542	0.8057	0.6068	411.69	21.98	0.0052	
Quadratic	1.98	0.9737	0.9550	0.8417	165.77	5.51	0.0664	Suggested
Cubic	1.52	0.9890	0.9737	0.6176	400.38	4.57	0.0993	Aliased
Average deflection								
Source	Standard deviation	R^2	Adjusted R^2	Predicted R^2	PRESS	F-value	p-value	Remark
Linear	0.15	0.8555	0.8266	0.5436	0.40	2.21	0.2315	
2FI	0.16	0.8571	0.8095	0.7120	0.45	2.61	0.1867	
Quadratic	0.14	0.9097	0.8452	0.7450	0.71	2.26	0.2234	Suggested
Cubic	0.15	0.9270	0.8249	-1.5776	4.00	4.71	0.0957	Aliased

Table 1 shows the statistical results for the HDPE-sawdust composite. As seen from the results, the quadratic model was chosen as the most appropriate model to predict the responses. This decision was reached based on the statistical parameters backing up the quadratic model. Among a number of alternatives, the model chosen should be the one with the desirable statistical parameters such as high R^2 value, low standard deviation, and low PRESS. The quadratic model was found to have the highest R^2 values for all the responses as shown in Table 1 for the HDPE composite.

Statistical analysis of the quadratic model was carried out. This was done by fitting the quadratic model to the experimental data obtained for all the responses. There was a total of 13 experimental runs (HDPE composite). After fitting the quadratic model to the experimental data, the model parameters were estimated to obtain the final model equations in terms of actual experimental factors. The model equations for the respective responses and the different composite materials are summarised as follows. The equations represent percentage elongation and average deflection, as a function of temperature (X_1) and level of polymer (X_2).

3.2 Statistical Analysis of Models

HDPE-Sawdust composite:

$$\textit{Percentage elongation} = -1562.08 + 0.17X_1 + 47.13X_2 - 0.00040X_1X_2 - 0.00031X_1^2 - 0.34X_2^2 \quad (4)$$

$$\textit{Average deflection} = 33.29 - 0.045X_1 - 0.69X_2 - 0.00020X_1X_2 + 0.000081X_1^2 + 0.0041X_2^2 \quad (5)$$

Equations 4 and 5 were used to predict the percentage elongation and average deflection, for the HDPE composite and the results are shown in Tables 2 for percentage elongation.

Table 2: Experimental and RSM predicted results for percentage elongation and average deflection (HDPE-sawdust composite)

Run	Factors				Response			
	Coded values		Actual values		Percentage elongation (%)		Average deflection (cm)	
	X_1	X_2	X_1	X_2	Experiment	Predicted	Experiment	Predicted
1	1	1	235.36	68.54	90.20	92.27	2.50	2.55
2	-1	1	164.64	68.54	88.50	90.98	2.30	2.46
3	0	0	200.00	65.00	84.80	85.70	2.80	2.76
4	-1	-1	164.64	61.46	70.10	69.78	3.20	3.32
5	1	-1	235.36	61.46	72.00	71.27	3.30	3.31
6	0	0	200.00	65.00	86.30	85.70	2.60	2.76
7	0	0	200.00	65.00	84.20	85.70	2.90	2.76
8	-1.414	0	150.00	65.00	85.10	83.94	3.10	2.93
9	1.414	0	250.00	65.00	86.50	85.91	3.00	2.99
10	0	-1.414	200.00	60.00	61.20	62.30	3.50	3.44
11	0	0	200.00	65.00	87.00	85.70	2.80	2.76
12	0	0	200.00	65.00	86.20	85.70	2.70	2.76
13	0	1.414	200.00	70.00	95.00	92.15	2.40	2.29

3.3 Analysis of Variance of Models

The fit of the statistical models representing the responses was assessed using analysis of variance (ANOVA). For the results presented, model terms with p values less than 0.05 is an indication that that term is significant. That means that changes in the values of the actual physical factor represented by that model term significantly affect the response in question. On the other hand, when the p value of any model term is greater than 0.05, it shows that the model term is not significant and changes in the values of the actual physical factor represented by that model term does not

significantly affect the response in question [11]. This suggests that the response models were significant and can be used for predictive purposes [12]Furthermore, the "lack of fit" p value for all the response models were greater than 0.05 indicating that the lack of fit was not significant. Significant lack of fit is not desirable as it implies that the model does not fit the experimental data.

The other statistical parameters that were used to assess the significance and fit of the response models are presented in Table 3. the models were characterised by high R^2 value and adjusted R^2 value. The R^2 value is used as an indication of model fit. The ideal R^2 value is unity in which case there is perfect fit between the experimental data and the model prediction. For the results reported in Table 4, the closeness of the R^2 value to unity indicates that the models were able to adequately represent the actual relationship between the variables considered in this study. Furthermore, the adjusted R^2 values obtained were within reasonable agreement with the corresponding R^2 values further confirming the fit of the models.

The models displayed very minimal standard deviation compared to the mean. This means that there was very little dispersion about the mean for the data predicted by the models [13]. This further corroborates the significant fit of the models. The coefficient of variation (C.V) obtained for the models were relatively small in magnitude. The coefficient of variation indicates the degree of precision with which the runs were carried out. A low value of C.V suggests a high reliability and reproducibility of the results [13]. The adequate precision values obtained were all greater than the recommended minimum value of 4 [14, 15] reported that the adequate precision measures the signal to noise ratio and a value greater than 4 is generally desirable and this means that the models can be used to navigate the design space.

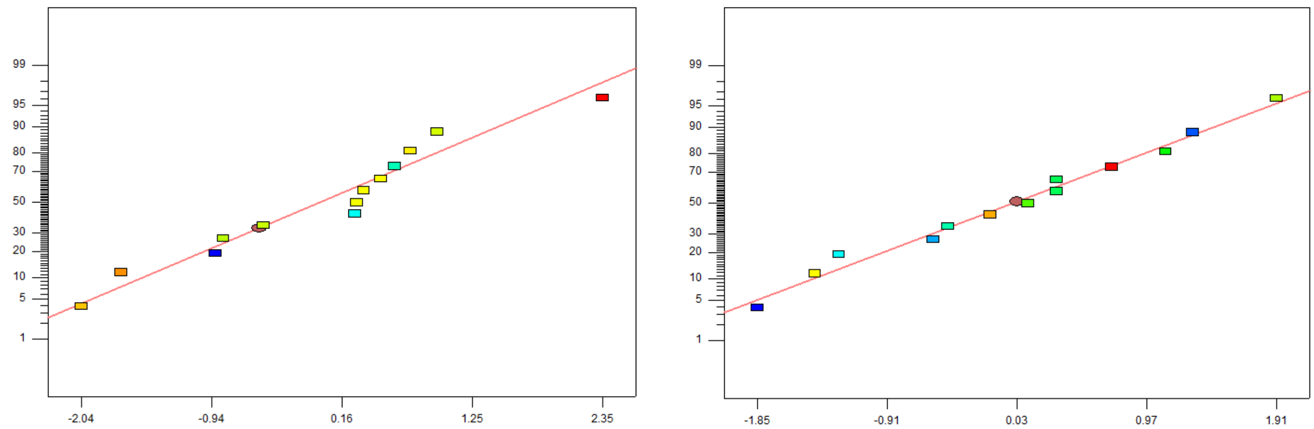
Table 3: Statistical information for ANOVA for quadratic models

Parameter	HDPE composite	
	Percentage elongation	Average deflection
R^2	0.9737	0.9097
Adjusted R^2	0.9550	0.8452
Mean	82.85	2.85
Standard deviation	1.98	0.14
C.V %	2.39	4.96
Adeq. Precision	22.257	11.971

3.4 Model Diagnostics

Model diagnostics was carried out to further assess the adequacy of the quadratic models developed to represent the responses and the results are presented in Figure 1.

Figures 1 shows the normal probability plots representing all the responses for the HDPE composites. This is an important plot which is used to determine whether the residuals follow a normal distribution. A desirable situation is when a normal distribution of the residuals is obtained and this is usually when all the points cluster around the straight line. Indeed, this was the case for the results presented in Figures 1 thus showing that the residuals followed a normal distribution.

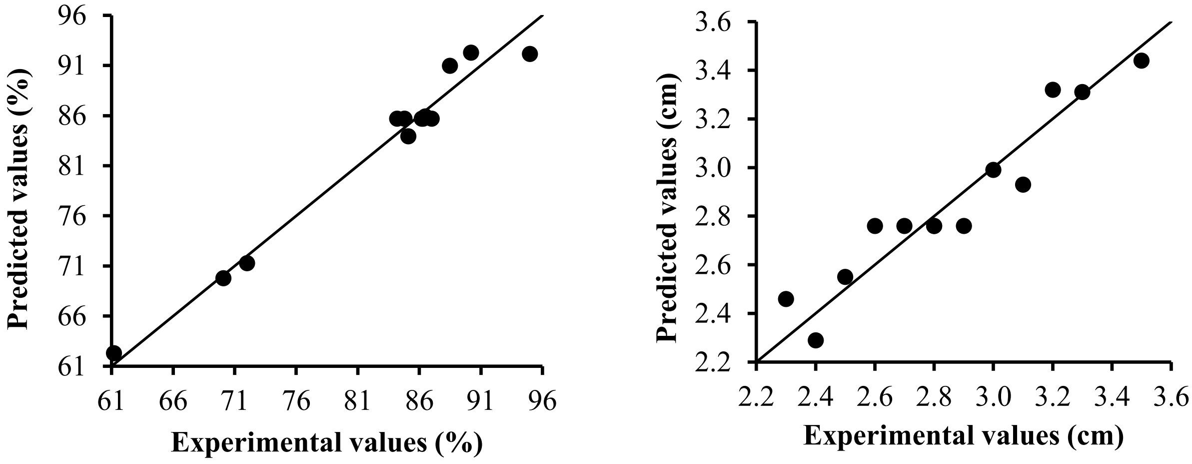


(a) (b)

Figure 1: Normal probability plot for (a) percentage elongation (b) average deflection for HDPE-sawdust composite

3.5 Validation of RSM Model Results

Figure 2 shows the parity plot for the HDPE-sawdust composites. This is a plot of the predicted response values versus the experimental response values. The purpose of this plot is to determine the predictive capacity of the models. The purpose is also to detect a value, or group of values, that are not easily predicted by the model. Comparison of the experimental values of the response and those predicted by the statistical models as shown in Figures 2 showed that there was an acceptable level of fit between the experimental and model predicted results. This is evident from the fact that the data points all clustered around the 45° diagonal line showing that there was minimal deviation between experimental and predicted values thus indicating optimal fit of the model.



(a) (b)

Figure 2: RSM parity plot for (a) percentage elongation (b) average deflection for HDPE-sawdust composite

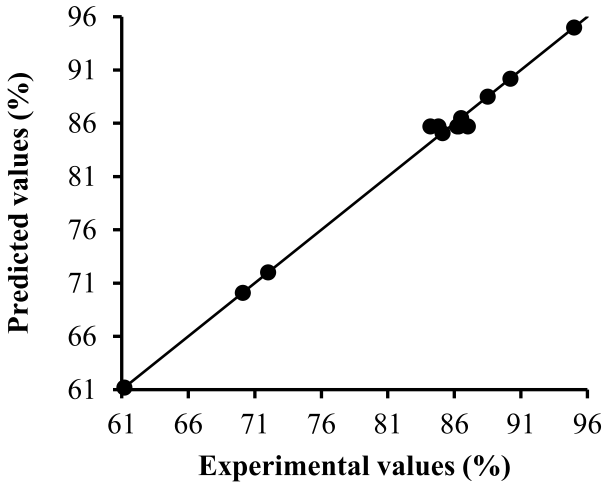
3.6 Validation of ANN Model Results

Validation of the ANN model was done by comparing the ANN predicted results with those obtained from the actual experiments and the results are presented for all the responses and composite materials in Table 4. It can be seen from the results presented that the values predicted by the ANN model were very close to the experimental values indicating validity and reliability of the ANN model.

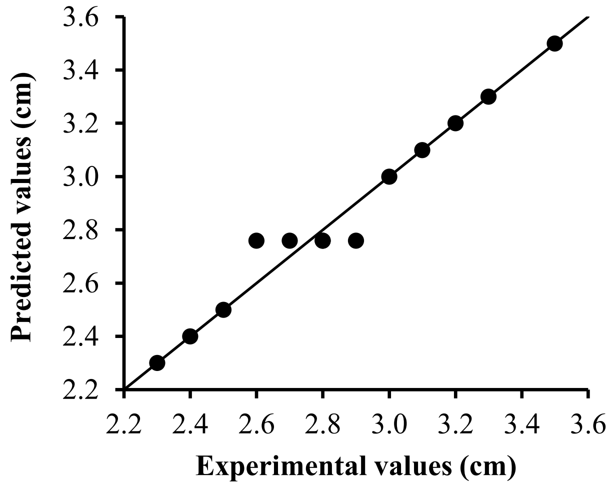
Table 4: Experimental and ANN predicted results for percentage elongation (HDPE composite)

Run	Factors				Response			
	Coded values		Actual values		Percentage elongation (%)		Average deflection (cm)	
	X_1	X_2	X_1	X_2	Experiment	Predicted	Experiment	Predicted
1	1	1	235.36	68.54	90.20	90.20	2.50	2.50
2	-1	1	164.64	68.54	88.50	88.50	2.30	2.30
3	0	0	200.00	65.00	84.80	85.70	2.80	2.76
4	-1	-1	164.64	61.46	70.10	70.10	3.20	3.20
5	1	-1	235.36	61.46	72.00	72.00	3.30	3.30
6	0	0	200.00	65.00	86.30	85.70	2.60	2.76
7	0	0	200.00	65.00	84.20	85.70	2.90	2.76
8	-1.414	0	150.00	65.00	85.10	85.09	3.10	3.10
9	1.414	0	250.00	65.00	86.50	86.49	3.00	3.00
10	0	-1.414	200.00	60.00	61.20	61.20	3.50	3.50
11	0	0	200.00	65.00	87.00	85.70	2.80	2.76
12	0	0	200.00	65.00	86.20	85.70	2.70	2.76
13	0	1.414	200.00	70.00	95.00	95.00	2.40	2.40

Figure 3 shows the parity plot of the responses for the HDPE-sawdust composite. It is a plot of the predicted response values versus the experimental response values. The purpose is to detect a value, or group of values, that are not easily predicted by the model. Comparison of the experimental values of the response and those predicted by the ANN model showed that there was an acceptable level of fit between the experimental and model predicted results. This is evident from the fact that the data points all clustered around the 45^o diagonal line showing that there was minimal deviation between experimental and predicted values thus indicating optimal fit of the model. Comparing these results with those presented in Figure 2 for the RSM prediction, it can be seen that the data points in Figure 3 clustered around the 45^o diagonal line closer than for the RSM results. This is an indication that the ANN model has better predictive capability compared to the RSM model.



(a)



(b)

Figure 3: ANN parity plot for (a) percentage elongation (b) average deflection for HDPE-sawdust composite

The goodness of fit statistics for the models representing tensile strength, proof stress, percentage elongation, average deflection, flexural strength and flexural modulus for the three composite materials are presented in Table 5. The values obtained indicate an excellent fit between the experimental and model predicted results. This is seen in the very high R^2 and adjusted R^2 values as well as the very small magnitude RMSE and AAD.

Table 5: Goodness of fit statistics for ANN

Parameter	HDPE composite	
	Percentage elongation	Average deflection
R^2	0.9949	0.9665
Adjusted R^2	0.9913	0.9426
RMSE	0.5177	0.0510
AAD	0.0028	0.0080

3.7 Comparison of RSM and ANN Performance

The accuracy RSM and ANN in predicting percentage elongation and average deflection is directly related to their predictive capability. The model with the better predictive capability will be able to predict the responses with a higher accuracy. The predictive capability of RSM and ANN was assessed using R^2 value, adjusted R^2 value, root mean square error (RMSE) and absolute average deviation (AAD) as shown in Table 6 for the HDPE-Sawdust composite. A good and accurate model prediction is usually characterised by high values of the R^2 value and adjusted R^2 value as well as very low RMSE and AAD. A comparison of the predictive capability of RSM and ANN as observed from the R^2 value, adjusted R^2 value, root mean square error and absolute average deviation shows that ANN performed better than RSM. This is because ANN gave very high R^2 values and adjusted R^2 values as well as very low RMSE and AAD values compared with RSM as shown in Table6.

Table 7: Comparison of RSM and ANN predictive performance (HDPE composite)

Parameters	% elongation		Aver. Deflection	
	RSM	ANN	RSM	ANN
R^2	0.9737	**0.9949**	0.9097	**0.9665**
Adj. R^2	0.9550	**0.9913**	0.8452	**0.9426**
RMSE	1.1717	**0.5177**	0.0835	**0.0510**
AAD	0.0095	**0.0028**	0.0206	**0.0080**

4 Conclusion

In this study central composite design was used to determine the various compositions (percentage volume) of the HDPE-sawdust composite at given temperatures. The composite was produced using the injection moulding process. Models were developed for predicting the mechanical properties (percentage elongation and average deflection) for the produced composites. The models were validated using coefficient of determination (R2). The coefficient of determination (R2) obtained ranged from 0.9213 (92.13%) to 0.981 (98.10%) which indicates that a substantial good fit was achieved by the model developed. Of the two methods examined artificial neural networks gave the optimal result.

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