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Modelling and Production of Injection Moulded Polyproplyn Sawdust Composite

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ABSTRACT

This study focuses on the modeling and production of the injection moulded Polypropylene - Sawdust (PP-sawdust) composite. The PP material and sawdust were mixed together to form a homogenous mixture with various percentage composition by volume as recommended by the central composite design (CCD). The two screw plunger injection moulding machine with maximum clamping force of 120 tons and shot capacity of 3.0oz was used to produce Polypropylene-Sawdust composite at various temperature. The produced composites were evaluated for their mechanical properties which included tensile strength, proof stress, percentage elongation and flexural strength. The response surface methodology (RSM) was used to determine the effect of the interaction of temperature, material type and percentage by volume of material on the mechanical properties of the produced PP-sawdust composite. Models were developed for predicting the mechanical properties (tensile strength, proof stress, percentage elongation and flexural strength) for the produced composites. The models were validated using coefficient of determination (R^2). The coefficient of determination (R^2) 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. A desirability of 0.952 was obtained which shows the adequacy of the model terms.

Keywords: Central composite design, Composite, Mahogany, Modeling, Polypropylene, Sawdust, tensile strength, proof stress.

INTRODUCTION

Injection moulding is a cost-effective way to produce complex, three dimensional shapes at high volumes. In the plastic industry, injection moulding makes up about 32% weight of all plastic processing methods, this is second only to extrusion which is 36% weight. Composite are man-made materials which are currently being used in wide application in the manufacture of industrial as well as consumer products (József and Tibor 2005)The deformable state achieved by plastic-sawdust composites at elevated temperature before chemically setting, allow them to be shaped to any intricate form. Injection moulding is a very complex process and its process variable like barrel temperature, injection pressure, the material flow rate, mould temperature and flow pattern usually influence the properties of polymeric materials.

According to this principle of combined action; new properties, better property combinations, or a higher level of properties are fashioned by the judicious combination of two or more distinct materials.A typical composite material is a system of materials comprising two or more materials (mixed and bonded) on a macroscopic scale. For example, concrete is made up of cement, sand, stones, and water. If the composition occurs on a microscopic scale (molecular level), the new material is then called an alloy for metals or a polymer for plastic (Acharya and Mishra 2007).

They carried out a study aimed to model fundamental bonding characteristics and performance of wood composite (Chunping et al, 2007). In their work, mathematical model and a computer simulation model were developed to predict the variation of inter-element (strand) contact during mat consolidation. The mathematical predictions and the computer simulations agree well with each other. Their results showed that the relationship between the inter-element contact and the mat density was highly nonlinear and was significantly affected by the wood density and the element thickness.

(Osarenmwinda and Nwachukwu, 2010) focused on the development of empirical models making use of previously obtained experimental data to estimate properties of produced composite material from agro waste). The empirical model was used to predict the properties of composite material (hardness, yield strength, ultimate tensile strength, modulus of elasticity, modulus of rupture, internal bond strength, density, thickness of swelling and water absorption) taking the inputs as percentage sawdust composition and percentage palm shell composition respectively.

(Njoku and Obikwelu 2008); examined the effect of reinforcement combination on the mechanical strength of glass reinforced plastic using compression moulding. A Proof stress of $29.52N/mm^2$ at a barrel temperature of 232^OC was obtained.(Westerdale and kazmer 2008), investigated the effects of temperature relative humidity and feedstock temperature on injection moulded part dimension and short term mechanical properties observed from tensile testing. The results indicated that environmental conditions influenced the moulded part quality to varying degrees and that the environmental conditions should be controlled for applications with tight tolerances. .

In Nigeria and other parts of the world, Agricultural products have not been integrated properly in engineering manufacturing and this have limited the growth in manufacturing as regard to the use of these local material. Agro-wastes products are natural raw material obtain from agricultural produce. In this research work, the Agro-wastes products used is: sawdust obtained from Agricultural plants (Mahogany).

Wood is sometimes defined as only the secondary xylem in the stems of trees, (Hejazi, et al 2012) or it is defined more broadly to include the same type of tissue elsewhere such as in tree roots or in other plants such as shrubs. In a living tree it performs a support function, enabling woody plants to grow large or to stand up by themselves. It also mediates the transfer of water and nutrients to the leaves and other growing tissues. Wood may also refer to other plant materials with comparable properties, and to material engineered from wood, or wood chips or fiber.

MATERIAL AND METHODS

Materials

The following materials were used for this work:

Polypropylene (PP), in powder form

Sawdust (from Mahogany tree obtained from saw mill in Benin City, Edo State

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

Methods

The method of approach through which the research objectives were actualized was reported in this chapter. The chapter starts with Research Design that described the planning and implementation of research work-scope.

Data Collection

In this study primary data were collected through performing of the experimnent using PP-Sawdust at the various proportions.

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 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 non linear models. The CCD is the only response surface design that can be used for planning experiments with two factors (Amenaghawon et al., 2014).

Models development

Design Expert® software version 7.0.0, (Stat-ease, Inc. Minneapolis, USA) was used to design the experiment and to analyze the experimental data obtained. The factors considered were temperature and the level of polymer (PP) in the matrix. The range and levels of these factors are shown in Tables 1 and was calculated using Equation (1). In generating the experimental design matrix, the Design Expert® software utilizes the concept of randomisation and the essence of this is to minimise the effect of unexplained variability in the chosen responses, (Montgomery 2005). In this case, the responses chosen for consideration were tensile strength, proof stress, percentage elongation, average deflection, flexural strength, and flexural modulus.

$$x_i = \frac{X_i - X_o}{\Delta X_i} \tag{1}$$

In Equation 1, x_i and X_i are the coded and actual values of the factors respectively while X_o is the actual value of the factors at the centre point, and ΔX_i is the step change in the value of the actual values of the factors.

In selecting the appropriate model for predicting the responses, different model types in the Design Expert software library were considered.

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The first type of model usually investigated is a linear model shown in Equation (2). It is usually proposed to predict the response of the dependent variables and to predict their optimum values when the relationship between the factors and the responses is thought to be linear.

$$Y = b_o + \sum_{i=1}^{N} b_i X_i + \sum_{i=1}^{N} e_i \tag{2}$$

Where Y_i is the dependent variable or predicted response, $X_i$is the independent variables, b_o is offset term, b_i is the regression coefficient and e_i is the error term.

Equation (3) is a two-factor interaction regression model which was also proposed to predict the response of the dependent variables and to predict their optimum values.

$$Y = b_o + \sum_{i=1}^{N} b_i X_i + \sum_{i,j=1}^{N} b_{ij} X_i X_j + \sum_{i=1}^{N} e_i \tag{3}$$

$X_j$is the independent variables or factors while b_{ij} is the coefficient of the interaction terms.

For situations where the relationship between the factors and the responses is thought to be nonlinear, a second order model as shown in Equation 4 can be used to predict the response.

$$Y = b_o + \sum_{i=1}^{N} b_i X_i + \sum_{i,j=1}^{N} b_{ij} X_i X_j + \sum_{i=1}^{N} b_{ii} X_i^2 + \sum_{i=1}^{N} e_i \tag{4}$$

The second order model is the most widely used model for response surface methodology (Carley et al. 2004).

Table 1: Coded and actual levels of the factors for PP polymer composite

Factors	Unit	Symbols	Coded and Actual Levels				
			-1.414	-1	0	1	1.414
Temperature	^oC	X_1	210.00	224.64	260.00	295.36	310.00
PP level	%	X_2	40.00	42.93	50.00	57.07	60.00

The data in Tables was used to generate their corresponding experimental design matrix by the Design Expert software and this resulted in 13 experimental runs as shown in Table 2.

Table 2: Experimental design matrix for PP polymer composite

Run	Factors	
	Temperature (^oC)	PP level (%)
1	260.00	50.00
2	295.36	42.93
3	295.36	57.07
4	310.00	50.00
5	260.00	40.00
6	260.00	60.00
7	224.64	42.93
8	210.00	50.00
9	224.64	57.07
10	260.00	50.00
11	260.00	50.00
12	260.00	50.00
13	260.00	50.00

RSM Data Verification

The predictive capability RSM was evaluated by comparing the results predicted by the RSM 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 (5) to (7) (Ajala and Betiku, Ajala, 2015).

$$R^2 = 1 - \sum_{i=1}^{n} \left(\frac{\left(y_{\exp} - y_{pred}\right)^2}{\left(y_{\exp} - y_{\exp,ave}\right)^2} \right) \tag{5}$$

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} \left(y_{pred} - y_{exp}\right)^2 \right)^{1/2} \tag{6}$$

$$AAD(\%) = \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_{\exp} - y_{pred}}{y_{\exp}} \right) \right) \times 100 \tag{7}$$

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 according to (Nath and Chattopadhyay, 2007). Generally, the closer the R^2 value is to 1, the better the level of fit between the experimental results and model predictions (Yi et al., 2009). 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 (Amenaghawon and Amagbewan, 2017)

The Moulding Process

The hydraulic and mechanical functions of the machine were checked and ascertained to be in order. Also, the mould and barrel heating functions, including the associated temperature sensors were checked.

The mould was then clamped on the platen and the heaters for the mould and barrel were switched on. The temperature control for the mould was set at 60^{o}C and that of the barrel at 150^{o}C. To encourage rapid heating, the mould was closed and the nozzle was allowed to rest slightly on the mould sprue opening in order to pick up some heat. The machine was left undisturbed for 30 minutes for the temperature to stabilize.

The moulding was performed with PP-Sawdust composite. When the temperature became stable, the electric pump that circulates the cooling water was switched on and then the hopper was loaded with PP-Sawdust composite. The temperature was regulated between 210 ^{o}C and 310 ^{o}C as recommended by the CCD when the plastic-Sawdust composite became molten. At this temperature, the cavities were completely filled using an injection pressure of 160 kg/cm^2. A clamping force of 12 tons was used, and before moulding at any temperature, an interval of 180 seconds was allowed for the temperature to stabilize.

RESULTS AND DISCUSSION

Modelling using Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing processes. It also has important applications in the design, development and formulation of new products as well as in the improvement of existing product designs(Raymond et al 2009).

Determination of Appropriate Model

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. Tables3 and 4 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 3: summary of model fit results (PP-Sawdust composite)

Tensile strength						
Source	Standard deviation	R^2	Adjusted R^2	Predicted R^2	PRESS	Remark
Linear	4.06	0.0289	0.0165	0.0161	323.34	
2FI	4.28	0.0289	0.0249	0.0152	429.50	
Quadratic	1.86	0.8579	0.7564	0.0470	170.83	Suggested
Cubic	0.66	0.9872	0.9692	0.2456	128.28	Aliased
Proof stress						
Source	Standard deviation	R^2	Adjusted R^2	Predicted R^2	PRESS	Remark
Linear	4.04	0.0339	0.01593	0.008	318.57	
2FI	4.25	0.0339	0.0288	0.0152	426.14	
Quadratic	1.83	0.8614	0.7625	0.0268	164.08	Suggested
Cubic	0.78	0.9821	0.9571	0.7404	169.85	Aliased

Table 4: Lack of fit test results (PP composite)

Tensile strength						
Source	Sum of square	degree of freedom	Mean square	F-value	p-value	Remark
Linear	164.95	6	27.49	610.93	< 0.0001	
2FI	164.95	5	32.99	733.10	< 0.0001	
Quadratic	23.98	3	7.99	177.65	0.081	Suggested
Cubic	2.00	1	2.00	44.44	0.0026	Aliased
Pure Error	0.18	4	0.045			
Proof stress						
Source	Sum of square	degree of freedom	Mean square	F-value	p-value	Remark
Linear	162.52	6	27.09	294.43	< 0.0001	
2FI	162.52	5	32.50	353.31	< 0.0001	
Quadratic	22.99	3	7.66	83.31	0.0510	Suggested
Cubic	2.64	1	2.64	28.75	0.0058	Aliased
Pure Error	0.37	4	0.092			

Tables 3 and 4, shows the statistical results for the PP-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 Tables 3and 4 PP-Sawdust composite. The quadratic model was also found to have the lowest standard deviation.

Statistical Analysis of Models

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 were a total of 13 experimental runs as shown in Tables 5 and 6 (PP-Sawdust 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 tensile strength, proof stress, percentage elongation, average deflection, flexural strength, and flexural modulus as a function of temperature (X_1) and level of polymer (X_2).

PP composite:

$$Tensile\ stress = -187.99 + 0.048X_1 + 9.13X_2 + 0.00010X_1X_2 - 0.000085X_1^2 - 0.092X_2^2 \quad (8)$$

$$Proof\ stress = -175.34 + 0.018X_1 + 8.72X_2 - 0.0010X_1X_2 - 0.000068X_1^2 - 0.085X_2^2 \quad (9)$$

$$Percentage\ elongation = -129.08 + 0.38X_1 + 5.30X_2 - 0.0099X_1X_2 + 0.00028X_1^2 - 0.018X_2^2 \quad (10)$$

$$Average\ deflection = -23.86 + 0.063X_1 + 0.75X_2 - 0.00020X_1X_2 - 0.000096X_1^2 - 0.0054X_2^2 \quad (11)$$

$$Flexural\ strength = 113.72 - 0.18X_1 + 0.84X_2 - 0.00070X_1X_2 + 0.00028X_1^2 - 0.021X_2^2 \quad (12)$$

$$Flexural\ modulus = -4.04 - 0.077X_1 + 0.67X_2 - 0.00020X_1X_2 + 0.00012X_1^2 - 0.0073X_2^2 \quad (13)$$

Equations 8 to13 were used to predict the tensile strength, proof stress, percentage elongation, average deflection, flexural strength, and flexural modulus for the PP-Sawdust composite and the results are shown in Tables 5 and 6 respectively. Similarly,

Table 5: Experimental and RSM predicted results for tensile strength, proof stress and percentage elongation (PP-Sawdust composite)

Run	Factors				Response					
	Coded values		Actual values		Tensile strength		Proof stress		Percentage elongation	
	X_1	X_2	X_1	X_2	Experiment	Predicted	Experiment	Predicted	Experiment	Predicted
1	0	0	260.00	50.00	33.70	33.50	43.60	43.48	81.00	80.16
2	1	-1	295.36	42.93	28.60	29.23	39.60	40.17	77.40	76.25
3	1	1	295.36	57.07	29.40	28.87	39.10	38.64	83.80	84.27
4	1.414	0	310.00	50.00	33.80	33.77	43.80	43.80	81.40	81.85
5	0	-1.414	260.00	40.00	25.50	24.60	36.60	35.68	68.20	69.42
6	0	1.414	260.00	60.00	23.30	24.03	33.70	34.23	88.20	87.13
7	-1	-1	224.64	42.93	28.50	29.20	38.60	39.46	71.00	70.38
8	-1.414	0	210.00	50.00	33.80	33.66	43.90	43.50	80.20	79.90
9	-1	1	224.64	57.07	29.20	28.75	39.10	38.93	86.40	87.40
10	0	0	260.00	50.00	33.70	33.50	43.30	43.48	80.40	80.16

11	0	0	260.00	50.00	33.50	33.50	43.10	43.48	79.60	80.16
12	0	0	260.00	50.00	33.20	33.50	43.50	43.48	79.50	80.16
13	0	0	260.00	50.00	33.40	33.50	43.90	43.48	80.30	80.16

Table 6 : Experimental and RSM predicted results for average deflection, flexural strength and flexural modulus (PP-sawdust composite)

Run	Factors				Response					
	Coded values		Actual values		Average deflection		Flexural strength		Flexural modulus	
	X_1	X_2	X_1	X_2	Experiment	Predicted	Experiment	Predicted	Experiment	Predicted
1	0	0	260.00	50.00	7.80	7.54	83.70	83.22	2.82	2.76
2	1	-1	295.36	42.93	5.60	6.21	90.20	90.27	2.56	2.48
3	1	1	295.36	57.07	8.20	8.34	75.80	74.76	2.60	2.58
4	1.414	0	310.00	50.00	7.90	7.48	83.50	83.95	2.90	2.94
5	0	-1.414	260.00	40.00	6.00	5.42	92.50	92.29	1.99	2.10
6	0	1.414	260.00	60.00	8.50	8.58	68.50	69.86	2.10	2.12
7	-1	-1	224.64	42.93	5.50	5.86	90.70	90.59	2.65	2.54
8	-1.414	0	210.00	50.00	7.20	7.13	83.20	83.90	2.80	2.89
9	-1	1	224.64	57.07	8.30	8.19	75.60	74.38	2.50	2.45
10	0	0	260.00	50.00	7.40	7.54	82.90	83.22	2.80	2.76
11	0	0	260.00	50.00	7.60	7.54	82.80	83.22	2.90	2.76
12	0	0	260.00	50.00	7.80	7.54	83.10	83.22	2.70	2.76
13	0	0	260.00	50.00	7.10	7.54	83.60	83.22	2.60	2.76

The suitability of the quadratic model for predicting the chosen responses was assessed by considering the standard error computed for each term of the model and the results are shown in Table 7. Low values of standard error like those shown in Table 7 are generally desirable and this is an indication that the model is suitable for the intended purpose. Furthermore, it is desirable that the standard errors should be similar within the same type of coefficient and this was the case observed for the results in Table 7. The results presented in Table 7 shows that the VIF obtained had a value of unity for almost all the terms in the model. The values of R_i^2 were observed to be between 0.0000 and 0.017 as shown in Table 7.

Table 7: Estimated standard error of quadratic model terms

Term	Standard error	VIF	R_i^2	Power at 5 % alpha level for effect of		
				0.5 Std. Dev.	1 Std. Dev.	2 Std. Dev.
X_1	0.35	1	0	9.40%	23.20%	68.10%
X_2	0.35	1	0	9.40%	23.20%	68.10%
X_1X_2	0.5	1	0	7.20%	14.00%	40.80%
X_1^2	0.38	1.02	0.017	20.80%	62.10%	99.40%
X_2^2	0.38	1.02	0.017	20.80%	62.10%	99.40%

Analysis of Variance of Models

The other statistical parameters that were used to assess the significance and fit of the response models are presented in Table 8. All 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 8, 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.

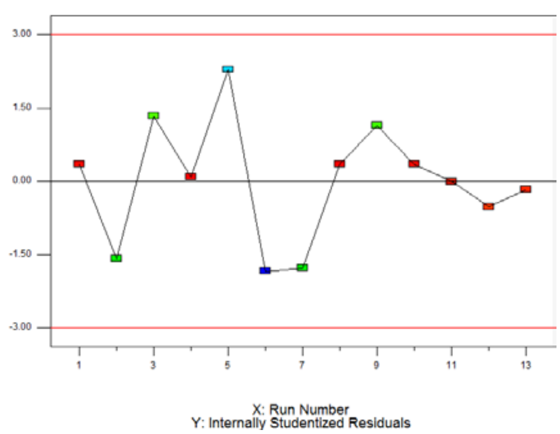
The models displayed very minimal standard deviation compared to the mean. This means that there was very little dispersion about the mean for the data predicted by the models (Khuri and Mukhopadhyay, 2010). This further corroborates the significant fit of the models. The coefficient of variation (C.V) 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 (Montgomery, 2005). The adequate precision values obtained were all greater than the recommended minimum value of 4 (Myers and Montgomery, 1995), (Cao et al. 2009), 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 8: Statistical information for ANOVA for quadratic models

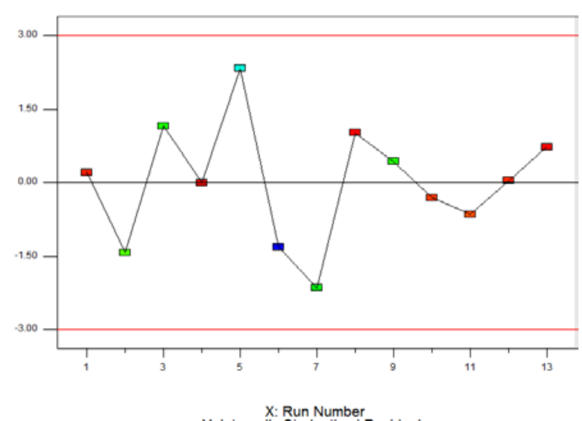
Parameter	PP composite					
	Tensile strength	Proof stress	Percentage elongation	Average deflection	Flexural strength	Flexural modulus
R^2	0.9810	0.9781	0.9791	0.8834	0.9887	0.8965
Adjusted R^2	0.9675	0.9625	0.9641	0.8000	0.9807	0.8226
Mean	30.74	40.91	79.80	7.30	82.78	2.61
Standard deviation	0.64	0.65	1.03	0.45	0.91	0.12
C.V %	2.10	1.59	1.29	6.15	1.10	4.55
Adeq. Precision	22.229	21.702	25.762	10.365	36.134	10.411

Model Diagnostics

Figure 1 show the plot of the residuals as a function of the experimental run order for the PP composites. This plot is useful for checking for any hidden variable that could have negatively impacted the responses during the experiments (Box et al., 2005). The ideal case should be a plot showing a random scatter. If this is not the case and there is a trend in the plot, it is an indication that there is a time-related variable hiding in the background. In such a situation, introducing blocking and randomization would be a way to solve the problem. The results presented in Figure1 show plots with a clear scatter indicating that the there is no hidden variable in the background that might negatively impact the results.



(a)



(b)

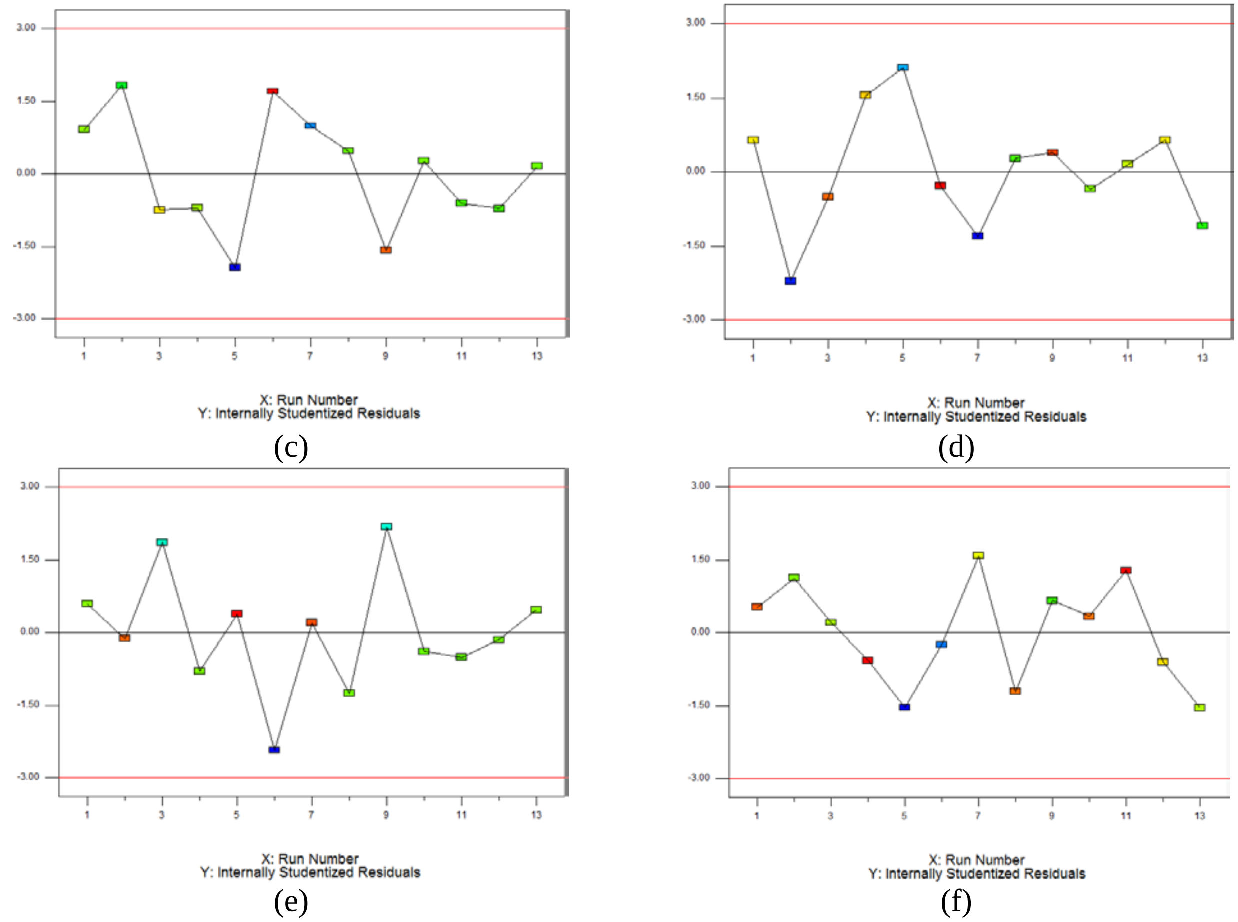


Figure 1: Plot of residuals versus experimental run order for (a) tensile strength (b) proof stress (c) percentage elongation (d) average deflection (e) flexural strength (f) flexural modulus For PP composite

Validation of RSM Model Results

Figure 2 shows the parity plot for the PP 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 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.

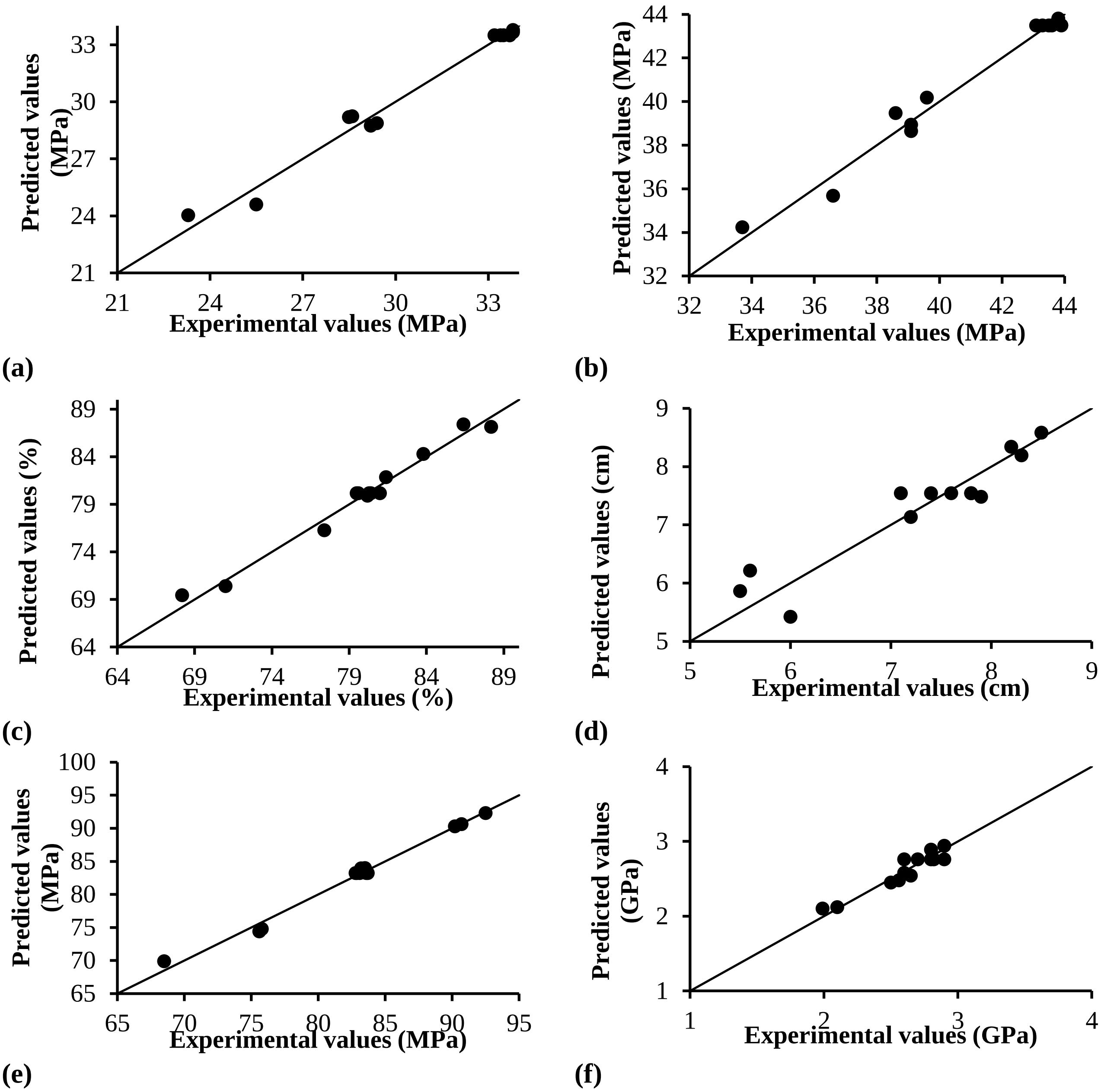


Figure 2: RSM parity plot for (a) tensile strength (b) proof stress (c) percentage elongation (d) average deflection (e) flexural strength (f) flexural modulus for PP composite

Conclusion

In this study central composite design was use to determine the various composition (percentage volume) of the plastic-sawdust composite at given temperatures.

Plastic sawdust composites PP-sawdust were produced using the injection moulding process.

Models were developed for predicting the mechanical properties (tensile strength, proof stress, percentage elongation and flexural strength) for the produced composites. The models were validated using coefficient of determination (R^2). The coefficient of determination (R^2) 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

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