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ORIGINAL RESEARCH ARTICLE

RESPONSE SURFACE OPTIMIZATION OF A PLASTIC POWDER PROCESSING MACHINE USING DESIRABILITY FUNCTION APPROACH

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ABSTRACT

Optimal performance and operational parameters of a plastic powder processing machine used for converting used PET bottles into powdered form was assessed in this study. The geometrical (operational) parameters investigated include: speed of hammermill shaft, number of blades on the hammermill, length of hammermill blade and intrinsic viscosity of the PET processed while grain size produced, throughput and conversion efficiency constitute the machine's (performance) parameters. The interactions of these factors (operational parameters) and responses (performance parameters) were evaluated and estimated using a completely randomized Box-Behnken blocked design layout which comprises twenty seven (27) experimental runs. Desirability function approach was the optimization technique applied. Results revealed the optimal values of hammermill speed, number of blades, blade length and intrinsic viscosity as 1400 rpm, 4, 109.6 mm and 0.82798 respectively with responses of 89.71%, 1.9953 kg/min and 139.9998 for conversion efficiency, throughput and grain size respectively. These optimal operational parameters will make the machine economical to operate in terms of labour, time and energy requirement.

1.0 Introduction

Plastics are non-biodegradable, synthetic polymers derived primarily from petro-fossil feedstock (fossil fuels) and made-up of long chain hydrocarbons with additives and can be moulded into finished products (Rosato, 2001). These polymers are broken in the presence of suitable catalyst, into monomers such as ethylene, propylene, vinyl, styrene and benzene. These monomers are then chemically polymerized into different categories of plastics.

Plastics are cheap, easy to manufacture, versatile, and unreceptive to water. Hence, their applications are vast ranging from paper clips to aircrafts. They have already displaced many traditional materials, such as wood; stone; horn and bone; leather; paper; metal; glass; and ceramics, in most of their former uses (Andrady and Neal, 2009).

Plastics are generally categorized as Thermoplastics and Thermoset Plastics. Thermoplastics can be melted to form new products which if re-heated, the product can melt again to form yet another new product. Some examples of thermoplastics include: LDPE, HDPE, PET, PVC, etc. Thermoset plastics also melt when heated to form new products but once they solidify, they cannot be re-melted to form another product like thermoplastics. These include Multilayer and

Laminated Plastics, Bakelite, Polycarbonate, Melamine, Nylon etc. (Luo et al., 2009). Hence, all thermoplastics can be recycled.

Plastic recycling involves recollecting waste plastic materials and processing them to form new and useful products. A lot of plastics are manufactured daily, causing the world's annual consumption of plastic materials to increase from around 5 million tons in the 1950s to nearly 100 million tons today (PlasticsEurope, 2008; Andrady, 2003). In Nigeria municipal solid waste contains 78% by weight of plastic waste (Abah, 2013). About eight million metric tonnes of plastic waste is poured into the ocean every year (Hardesty and Wilcox, 2015; Jambeck et al., 2015). Hence, recycling is a global effort to moderate plastic in the waterways since plastic is non-biodegradable.

Plastic recycling includes taking any type of plastic sorting it into different polymers, chipping it and then melting it down into pellets. After sorting, they are crushed into tiny pieces and then melted to form pellets which can be used to create items of any kind such as plastic bottles, bowls, chairs, tables, depending on the choice of the manufacturer and the type of plastic processed.

However, since the discovery of 3D printing, there has been high demand for plastic in powdered form for easy manufacturing (3D printing) of components/parts. Other advantages of plastic powder include: less storage space, easy/cheap transportation and possibility of plastic coating of materials. For this reason, the plastic powder processing machine was developed. According to Nwogu et al. (2019), the machine is capable of crushing used plastics (especially PET bottles) into powdered form which is used as feedstock for 3D printing. Determination of the optimal operational parameters of this machine will make its use economical in terms of labour, time and energy requirement.

Response Surface Methodology (RSM) is a set of statistical and mathematical technique which uses quantitative data from appropriate experimental designs to determine and simultaneously solve/analyze multi-variant models with the objective of finding the optimal settings of input factors or design variables that maximize or target some performance measures/quality characteristics or responses (Myer and Montgomery, 2002; Buyske and Trout, 2009). RSM is a critical technology in designing, formulating, developing, and analyzing new scientific studies and also efficient in the improvement of existing ones. Thus, Kathleen et al. (2004), wrote that RSM is a collection of statistical and mathematical techniques useful for developing and optimizing systems. Optimal operational settings determined using RSM are always or nearly close to the optimal operating conditions of the true system (Oehlert, 2000; NIST/SEMATECH, 2006).

The main objective of this work is the optimization of a plastic powder processing machine using desirability function approach. This involves development of appropriate response surface model, as well as optimization of the fitted response equations.

2.0 Materials and Method

2.1 Materials

The plastic powder processing machine evaluated was developed by Nwogu et al. (2019). The machine comprises of the following parts (Figure 1): the frame, electric motor, melting pot, barrel, blower, tray, hammermill, crank mechanism and a temperature control circuit.

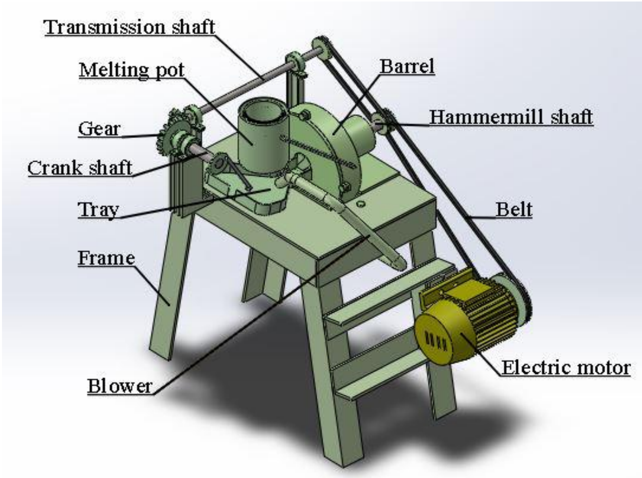

Figure 1: Isometric view of the machine (Nwogu et al., 2019).

Materials/devices used in the optimization of the machine include: Vernier calliper, measuring tape, PC, Minitab software, sieve.

Two grades of PET bottles i.e. PET1 with intrinsic viscosity values ranging from 0.78-0.80 (used for water bottles) and PET2 with intrinsic viscosity values ranging from 0.80-0.85 (used for carbonated drinks bottles) were used for this evaluation.

2.2 Method

The determination of the optimal settings of the performance and operational parameters of the machine involves model selection, experimental design, data collection, model fitting, model validation and optimization. The empirical relationships between the performance and operational parameters of the machine were evaluated using a response surface design generated with MINITAB software.

The design used is a completely randomized Box-Behnken blocked design comprising of twenty seven (27) experimental runs based on four factors: speed of the hammermill shaft, number of blades on the hammermill, length of hammermill blade and intrinsic viscosity (grade) of PET processed. The high, low and centre levels of the factors were determined from physical measurement and the limits are shown in Table 1.

Table 1: Limits of the machine operational parameters

S/N	Factor Description	Factor Symbols		Factor Values		
		Coded	Actual	High (+1)	Low (-1)	Centre (0)
1	Speed of hammermill shaft (rpm)	X_1	N_2	2300	1400	1850
2	Number of blades on the hammermill	X_2	n	8	3	5.5
3	Length of hammermill blade (mm)	X_3	lb	115	95	105
4	Intrinsic viscosity of PET processed	X_4	w	0.85	0.78	0.815

The machine was run with different grades of PET at different hammermill speeds while varying the length and number of blades on the hammermill. The performance of the machine at each factor combination was recorded. Throughput and conversion efficiency for the different factor combinations were calculated from Equations 1 and 2 respectively while grain size for each factor combination was obtained by passing the powder through sieves of different mesh sizes arranged vertically. The transformation formulae relating the coded and actual values of the factors are shown in Equations 3-6.

$$\mathrm{TP} = \frac{\mathrm{M}}{\mathrm{T}} \qquad (1)$$

where:

M = Mass of the plastic powder produced, (kg)

T = Production time, (h)

$$\eta_c = \frac{\text{quantity of powder produced (Kg)}}{\text{quantity of PET processed (Kg)}} \times 100\% \quad (2)$$

$$x_1 = \frac{N_2 - 1850}{450} \quad (3)$$

$$x_2 = \frac{n - 5.5}{2.5} \quad (4)$$

$$x_3 = \frac{l_b - 105}{10} \quad (5)$$

$$x_4 = \frac{\omega - 0.815}{0.035} \quad (6)$$

The completely randomized Box-Behnken blocked design layout used in this investigation is shown in Table 2.

Table 2: Design table for the response surface study of the developed machine

Design order				Coded factors				Responses		
Std Order	Run Order	PtType	Blocks	X_1	X_2	X_3	X_4	Grain Size	Throughput	Conversion Efficiency
6	1	2	1	0	0	1	-1	140.0	1.37	0.84
20	2	2	1	1	0	1	0	5.0	1.35	0.74
7	3	2	1	0	0	-1	1	180.0	1.56	0.79
19	4	2	1	-1	0	1	0	150.0	2.12	0.89
18	5	2	1	1	0	-1	0	10.0	1.24	0.65
26	6	0	1	0	0	0	0	75.0	1.67	0.81
24	7	2	1	0	1	0	1	114.0	2.31	0.80
15	8	2	1	0	-1	1	0	90.0	1.38	0.78
16	9	2	1	0	1	1	0	40.0	1.39	0.84
17	10	2	1	-1	0	-1	0	111.0	1.01	0.86
21	11	2	1	0	-1	0	-1	110.0	1.16	0.69
10	12	2	1	1	0	0	-1	60.0	0.92	0.64
9	13	2	1	-1	0	0	-1	120.0	1.85	0.93
3	14	2	1	-1	1	0	0	158.0	2.14	0.88
14	15	2	1	0	1	-1	0	30.0	1.51	0.75
8	16	2	1	0	0	1	1	50.0	1.56	0.83
23	17	2	1	0	-1	0	1	25.0	1.31	0.78
11	18	2	1	-1	0	0	1	170.0	2.86	0.91
27	19	0	1	0	0	0	0	75.0	1.67	0.81
25	20	0	1	0	0	0	0	75.0	1.67	0.82
1	21	2	1	-1	-1	0	0	200.0	1.40	0.85
5	22	2	1	0	0	-1	-1	15.0	1.16	0.69
12	23	2	1	1	0	0	1	10.0	1.07	0.65
22	24	2	1	0	1	0	-1	80.0	1.39	0.82
13	25	2	1	0	-1	-1	0	115.0	1.55	0.79
4	26	2	1	1	1	0	0	3.9	1.00	0.84
2	27	2	1	1	-1	0	0	25.0	0.92	0.73

The response surface design shown in Table 2 was analyzed using MINITAB to estimate quadratic (response surface) models of the form (Equation 7):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_{ii}^2 + \sum_{i<j}^{\frac{k(k-1)}{2}} \beta_{ij} x_i x_j + \epsilon \quad (7)$$

Where y represents each of the responses in their natural forms, x represents each of the factors in their coded forms, β represents the coefficient of each term of the models, k represents number of factors in the models, ϵ represents error in each estimate, i = 1,2,...,k and j>i. Then analyses of variance, lack-of-fit test and residual analyses were conducted using MINITAB to check the adequacy of the estimated models to approximate the measured data well at 95% confidence interval.

If Fcal > Ftab and p-val > 0.05, the models are adequate approximation of the measured data; if FcalLOF > FtabLOF and p-valLOF > 0.05, the models have no significant lack-of-fit. Also, if the residuals tend towards an 'S' shape along a straight line with minimum number of outliers in the normal probability plots the more the adequacy of the fitted models. Also if the residuals are normally distributed along the mean lines of the residuals versus fitted value and residual versus observation order with little or no cluster, the models are adequate, and little or lack of skewness and outliers in the histogram shows that the models are adequate. Finally coefficients of determination (R2 and adj – R2) and error standard deviation (S) were determined to check the goodness of fit of the models. The more R2 and adj – R2 approximate to 100% and the smaller the value of S and the better the models approximate the measured data well.

3.0 Results and Discussion

The developed coded responses functions of the machine investigated are as follows (Equations 8-10).

$$S_g = 82.85 - 66.26x_1 - 11.59x_2 + 1.17x_3 + 2.00x_4 + 29.7x_2x_4 - 63.8x_3x_4 \quad (8)$$

$$TP = 1.5015 - 0.4067x_1 + 0.2350x_4 \quad (9)$$

$$\eta_c = 0.79296 - 0.0892x_1 + 0.0325x_3 \quad (10)$$

These coded functions were converted into the following actual response functions of the machine from the transformation formulae shown in Equations 3-6.

$$S_g = 148.69l_b + 17330.72\omega + 339.43(n * \omega) - 0.147N_2 - 281.28n - 182.29(l_b * \omega) - 13757 \quad (11)$$

$$TP = 6.71\omega - 0.000904N_2 - 2.299 \quad (12)$$

$$\eta_c = 0.00325l_b - 0.000198N_2 + 0.8180 \quad (13)$$

The standardized residual plots which include the normal probability plot, histogram, residual versus fitted value and residual versus observation order are shown in Figures 2 to 4.

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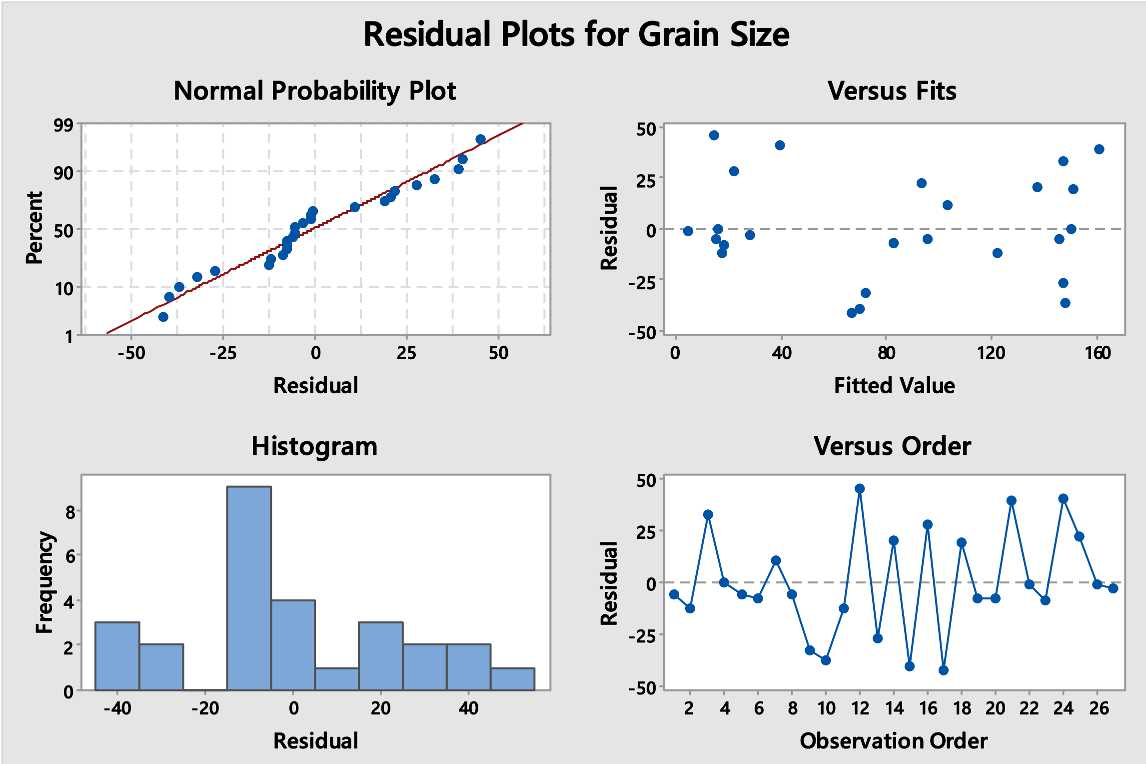

Figure 2: Residual plots for the machine's grain size model

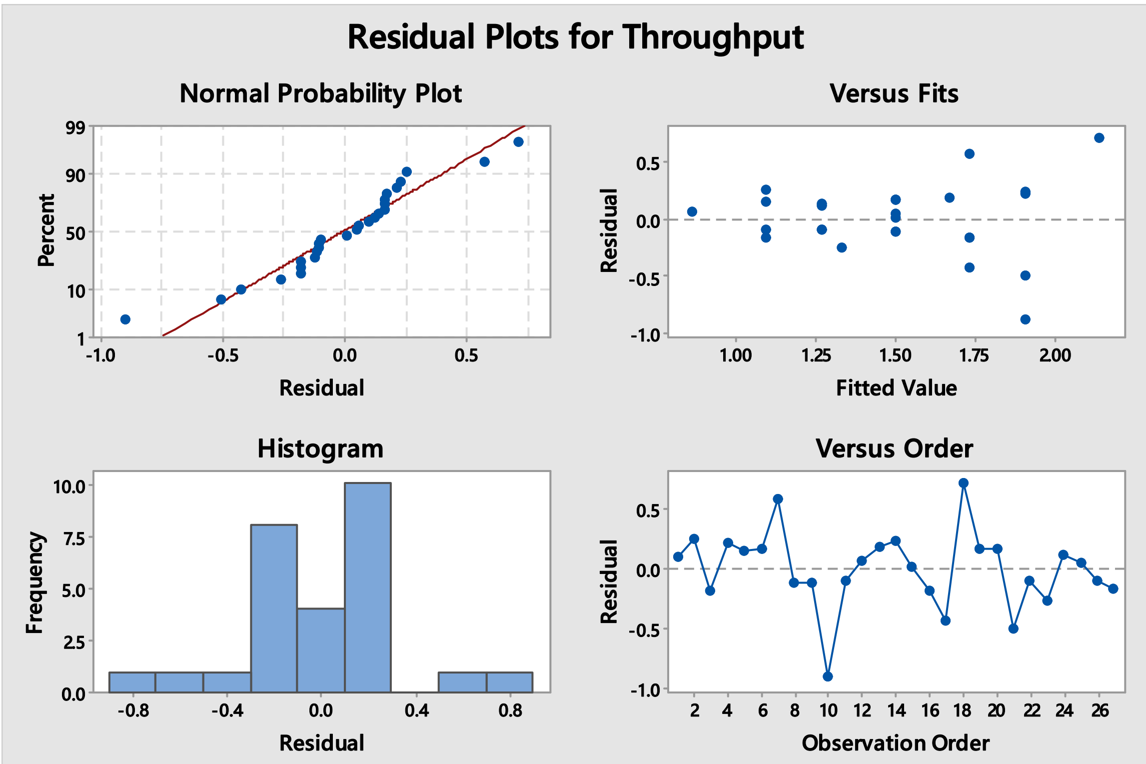

Figure 3: Residual plots for the machine's throughput model

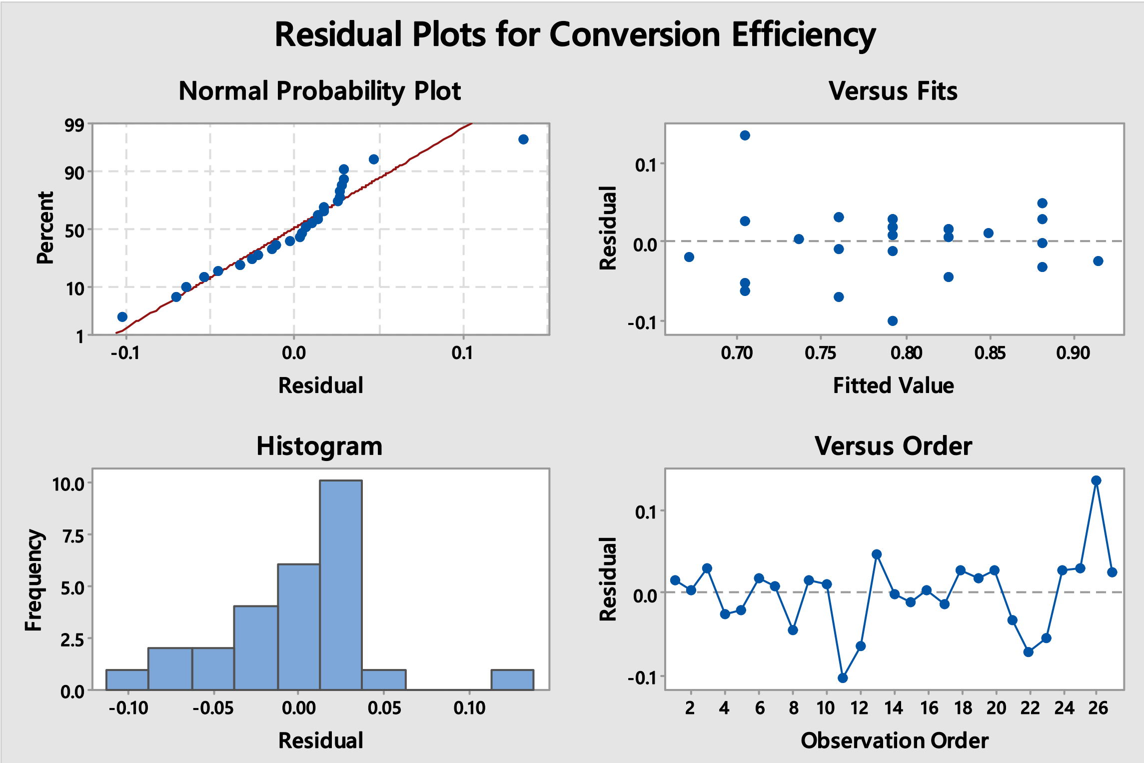

Figure 4: Residual plots for the machine's conversion efficiency model

According to Buyske and Trout (2009), Figures 2 to 4 indicate that the developed models statistically fitted the machine's responses adequately since:

The residuals approximate or form 'S' shape along a straight line in all the three responses.

The normal probability plots of the grain size, throughput and conversion efficiency of the developed machine has little or no outliers.

The residuals are normally distributed along the mean lines of the residuals versus fitted values as well as residuals versus observation order with very minimal cluster in all the three responses.

The developed models were used to predict values of grain size, throughput and conversion efficiency and these predicted values were compared with the actual values derived experimentally (Table 3).

Table 3: Determination of the prediction accuracy of the response models

Run Order	X_1	X_2	X_3	X_4	Actual Values S_g	Actual Values TP	Actual Values η_C	Predicted Values S_g	Predicted Values TP	Predicted Values η_C	Percentage Error S_g	Percentage Error TP	Percentage Error η_C
1	0	0	1	-1	140.0	1.37	0.84	145.85	1.32	0.83	-4.2	3.6	1.2
2	1	0	1	0	5.0	1.35	0.74	5.2	1.32	0.74	-4.0	2.2	0
3	0	0	-1	1	180.0	1.56	0.79	179.1	1.59	0.76	0.5	-1.9	3.8
4	-1	0	1	0	150.0	2.12	0.89	150.3	2.09	0.91	-0.2	1.4	-2.2
5	1	0	-1	0	10.0	1.24	0.65	10.2	1.20	0.67	-2.0	3.2	-3.1
6	0	0	0	0	75.0	1.67	0.81	76.1	1.62	0.79	-1.5	3.0	2.5
7	0	1	0	1	114.0	2.31	0.80	113	2.29	0.79	0.9	0.9	1.3
8	0	-1	1	0	90.0	1.38	0.78	91	1.40	0.80	-1.1	-1.4	-2.6
9	0	1	1	0	40.0	1.39	0.84	42	1.41	0.83	-5.0	-1.4	1.2
10	-1	0	-1	0	111.0	1.01	0.86	112	1.03	0.85	-0.9	-2.0	1.2
11	0	-1	0	-1	110.0	1.16	0.69	111	1.20	0.70	-0.9	-3.4	-1.4
12	1	0	0	-1	60.0	0.92	0.64	58	0.91	0.66	3.3	1.1	-3.1
13	-1	0	0	-1	120.0	1.85	0.93	121	1.82	0.90	-0.8	1.6	3.2
14	-1	1	0	0	158.0	2.14	0.88	153	2.12	0.88	3.2	0.9	0
15	0	1	-1	0	30.0	1.51	0.75	31	1.50	0.76	-3.3	0.7	-1.3
16	0	0	1	1	50.0	1.56	0.83	48	1.6	0.83	4.0	-2.6	0
17	0	-1	0	1	25.0	1.31	0.78	26	1.35	0.79	-4.0	-3.1	-1.3
18	-1	0	0	1	170.0	2.86	0.91	168	2.83	0.88	1.2	1.0	3.3
19	0	0	0	0	75.0	1.67	0.81	76.1	1.62	0.79	-1.5	3.0	2.5
20	0	0	0	0	75.0	1.67	0.82	77.1	1.61	0.79	-2.8	3.6	3.7
21	-1	-1	0	0	200.0	1.40	0.85	198	1.42	0.88	1.0	1.4	-3.5
22	0	0	-1	-1	15.0	1.16	0.69	15.2	1.19	0.71	-1.3	-2.6	-2.9
23	1	0	0	1	10.0	1.07	0.65	10.3	1.10	0.67	-3.0	-2.8	-3.1
24	0	1	0	-1	80.0	1.39	0.82	78	1.34	0.79	2.5	3.6	3.7
25	0	-1	-1	0	115.0	1.55	0.79	113	1.50	0.76	1.7	3.2	3.8
26	1	1	0	0	3.9	1.00	0.84	4.0	1.01	0.81	-2.6	-1.0	3.6
27	1	-1	0	0	25.0	0.92	0.73	25.8	0.94	0.70	-3.2	-2.2	4.1

Results of the confirmatory tests for grain size, throughput and conversion efficiency are displayed in Figures 5 to 7.

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Figure 5: Confirmatory test for grain size

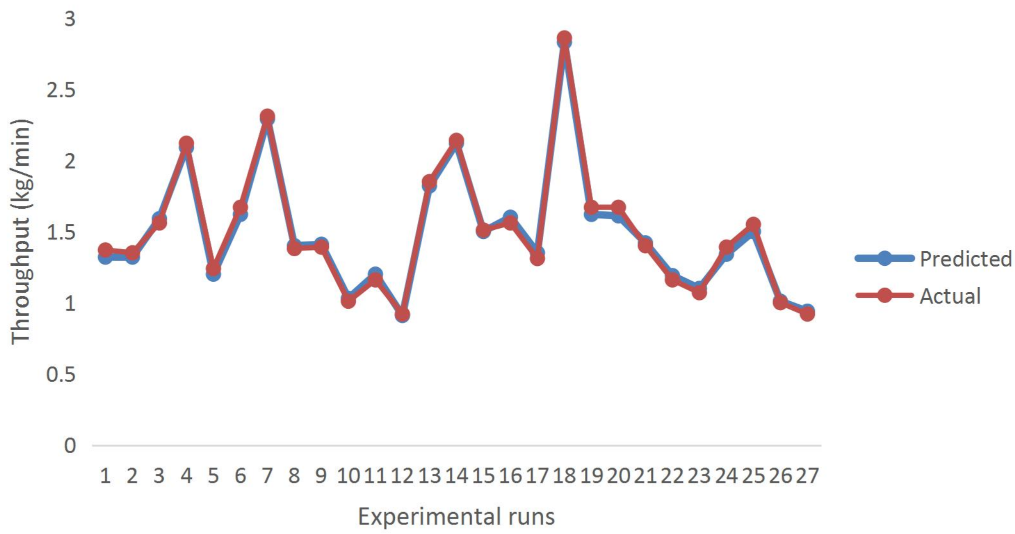

Figure 6: Confirmatory test for throughput

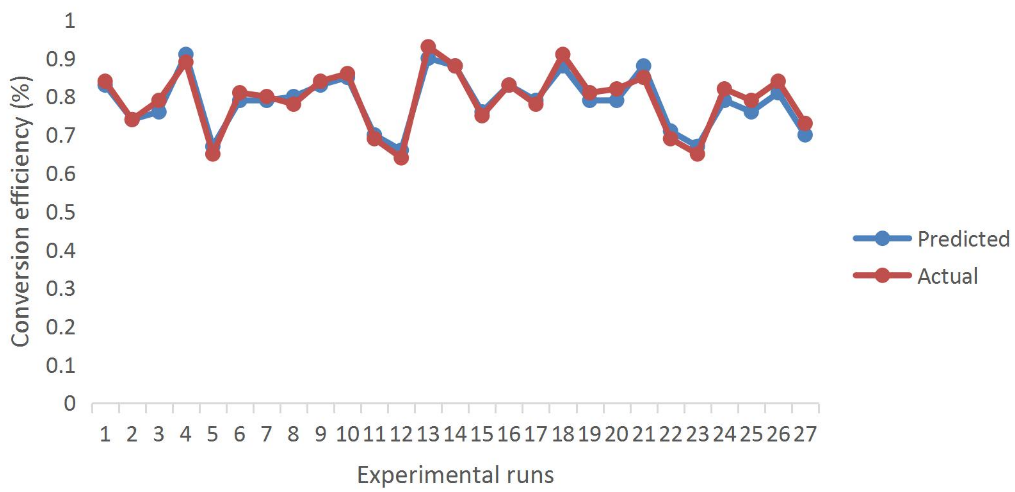

Figure 7: Confirmatory test for conversion efficiency

Figures 5 to 7 show very close relationship between predicted and actual values of the responses. Hence, the model has very high prediction accuracy with less than 5% error in all the predicted values (Table 3). This is in line with Oehlert, (2000) and NIST/SEMATECH (2006) statements that 'equations and optimal operational settings determined using RSM are always or nearly close to the optimal operating conditions of the true system'

These fitted functions were further used for optimization of the system. The optimization result is shown in Figure 8.

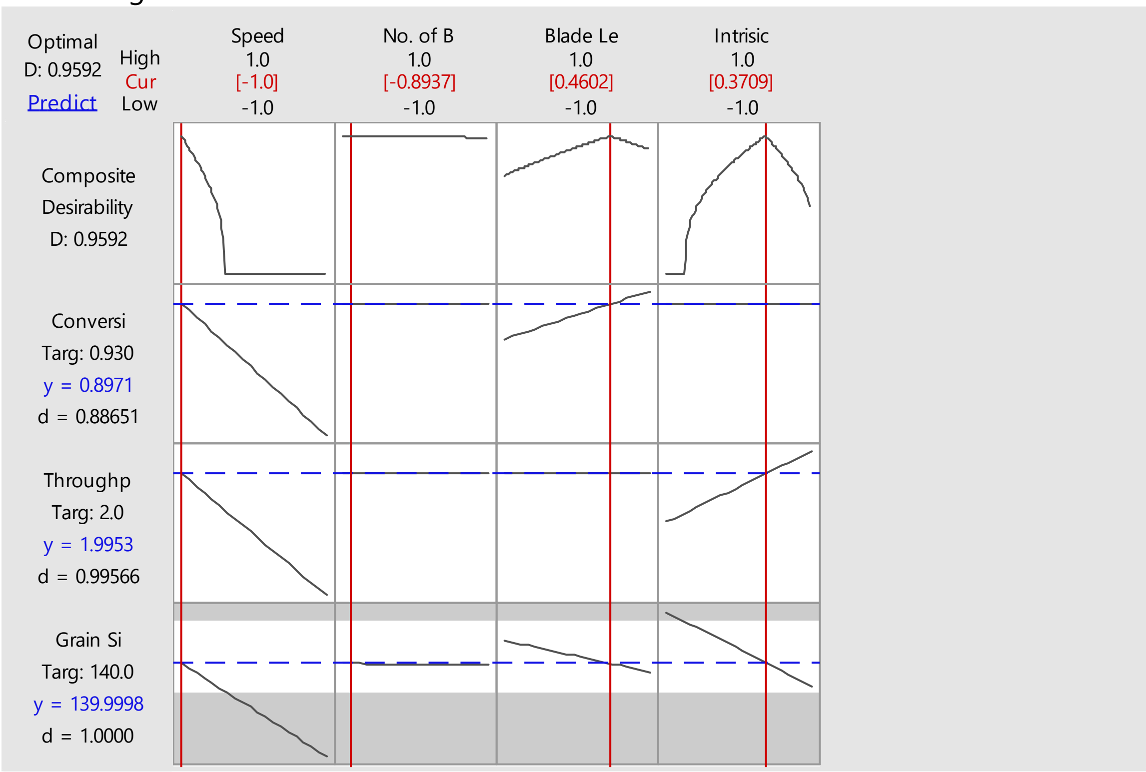

Figure 8: Optimization plot for the machine performance parameter models

Figure 8 shows the optimal setting of overall conversion efficiency, throughput and grain size to be approximately 89.71%, 1.9953 kg/min and 139.9998 respectively, with coded input variables at -1.0, -0.8937, 0.4602 and 0.3709. Substituting these coded optimal values in the transformation equations give the approximate optimal values of speed, number of blades, blade length and intrinsic viscosity as 1400 rpm, 4, 109.6 mm and 0.82798 respectively.

4.0 Conclusion

A plastic powder processing machine capable of converting used PET bottles into powdered form was optimized..

Response surface optimization of the developed machine showed the optimal setting of conversion efficiency, throughput and grain size as 89.71%, 1.9953 kg/min and 139.9998 respectively. Hence, optimal values of hammermill speed, number of blades, blade length and intrinsic viscosity were determined as 1400 rpm, 4, 109.6 mm and 0.82798 for respectively. These optimal operational parameters will make the machine economical to operate in terms of labour, time and energy requirement as well as improve the machine's output.

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