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Optimization Through Artificial Neural Network and Compare with Response Surface Methodology for Multiples Yield

Khadija Tariq[1], Naheeda Perveen[2], Hafiz Shabir Ahmad[3]

Abstract

Cotton slub yarn is widely used in denomination and any other casual, physical and mechanical Conditions. The data for the underlying purpose was collected from the Department of Polymer Engineering, National Textile University, and Faisalabad. R-Programming language software is used for analysis. The output of cotton depends on several factors whose cumulative influence on Process efficiency has a direct influence. The purpose of the research was to optimize the 100% cotton slub yarn model (slub length, slub thickness, pause length and linear density) for multiples yield (elongation, imperfection, strength, coefficient of mass variation and hairiness) as Optimizing is a way of identifying and enhancing the performance of the constructed framework by assessing a set of quality parameters, such as process efficiency using two methods response- surface methodology (RSM) and artificial neural network (ANN) and the results are compared using mean square error (MSE). Furthermore, coefficients of determination () and the mean square error root (RMSE) are used for greater accuracy. However, the ANN has consistently performed better than the RSM in all the aspects. The final selected ANN model was able to simultaneously predict the five output parameters with an RMSE of 0.229.

Keywords: artificial neural network, response surface

1. Introduction

Cotton, which provides a 35% share of total worldwide fibers, is one of the most essential fiber and oleaginous crops. China is one of the nation's biggest agricultural commodities so cotton is more important to China. The output of cotton depends on several factors whose cumulative influence on process efficiency has a direct influence. Thus, an effective numerical equation should be chosen for both prediction and improvement. Optimizing is a way of identifying and enhancing the performance of the constructed framework by assessing a set of quality parameters, such as process efficiency. The enhancement of the bio massing cycle is aimed at deciding the unique circumstances (ecological and/or design dimensions). Experiments are usually performed so as to apply and evaluate certain elements, while another remains uninfluenced (Wang *et al*., 2020).

1.1. Yarn

The basic unit of textile is fabric. Fabric is interlocked to make yarn. It can be said that with extended unbroken length yarn is dovetailed fabric. In the textile production sewing, embroidery, knitting, rope making and waving pattern are used to make yarn.

1.2. Slub

Thicker section along yarn is called slub.

1.3. Slub Yarn

A yarn that has spun with slubs is called yarn. Slub yarn is purposefully created to give more personality to a fabric. Yarn is a long lengthen continuous interlock fiber, which is made out of both natural and synthetic fibers. Using Slub yarns one can even produce. There are yarn manufacturers all over the world who exports these yarns to different places.

1.4. Fabric

Fabric is kind of material which is formed by weaving and combining by different threads. Curtains, clothes and sheets are all kin of fabric. By using synthetic and natural thread fabric is constructed. The traditional methods to construct fabric are knitting, non-woven and weaving.

1.5. Woven fabric

Among one of the traditional and old technique is weaving. As compared to all categories of fabric woven fabrics are originate longer in their dimensional solidity. Weaving methods consist of two different collections of yarn are interwoven vertical to form a cloth or fabric.

These are three types of woven.

- Plain
- Twill
- Stain

Fabric properties have:

- Strength
- Crease
- Fall
- Color-fastness
- Tearing
- Stiffness

1.6. Different types of slub yarn

Depending on thickness and slub length the yarn can be classified into two different types. Some useful information regarding these two varieties is explained below.

Multi-count yarn: when it comes to multi count yarn, then number of threads changes whereas number of twists remains unaltered. This leads to spinning variation in the fabric that provides an excellent color combination.

[1] Lecturer, The University of Faisalabad, Pakistan, khadijatariq458@gmail.com
[2] Lecturer, The University Faislabad, Pakistan, naheeda.perveen@tuf.edu.pk
[3] Lecturer, The University Okara, Pakistan, hafizshabirahmad786@gmail.com

Multi-twist yarn: in this type slub yarn the number of yarn remains same but the number of twist changes. Owing to this variation leads to different texture in the fabric and color also gets altered

1.7. Slub Yarn Nature

A slub yarn is the one that is spun with the intention of completing an irregular shape both in length and diameter. Traditionally, slubbed fabric considered defective and poor quality. Contemporary spinning equipment makes it possible to create smooth, and in even yarns without imperfections. Slubs are not a defect in the fabric and are not considered a fault they are a part of the Character of the fabric.

2. Response Surface Methodology (RSM)

RSM is a collection of analytical techniques for developing processes that enhance and maximize interest responses, and the aim is to improve these responses. Response Surface Technique is one of the best practices of the last two decades. It has significant uses in designing, developing, commercializing and enhancing core product models (Bas and Boyacı 2007; Zanden, 2023). The empirical optimization techniques for RSM implementations were proposed by (Bezerra et al., 2008). Optimization is used to optimize operation, item, or device efficiency to achieve the gain. In analytical chemistry, the optimization process is widely used for obtaining the optimal possible answer. In RSM empirical-based models are used by mathematical and statistical skills. In order to implement multivariate statistical methods, the theoretical work and its applications of RSM have been identified. RSM comprises much more than the fitting and study of the second-order model. The RSM has been a major part of industrial experimental work and is widely understood.

Box and Liu (1999) reported that RSM was being applied to the common helicopter-training example. A retrospective on the roots of RSM is given by Box (1999). Three detailed assessments of the answer surface approach have been conducted over the past 50 years. In the Biometrics review paper, Mead and Pike (1975) concentrate on biological data modeling rather than RSM discussion as we understand it. Myers *et al*., (1989) have been the latest review article they stressed changes occurring during the 1970s and 1980s in RSM principles and application. In the last decade, these advances have increased the use of developed experimentation. In the area of research, software advancement, including important improvements in multiple reaction optimizations, was definitely beneficial (Myers *et al*., 2004).

RSM is a collection of statistical and mathematical methods that are used to create model of some kind of proper functional relationship of response of interested variable and a few concerned controlled variables. Normally that unknown relationship is approximated by using a low order polynomial equation (Khuri and Mukhopadhyay, 2010).

Response surface approach has two major designs.

(i) Central composite design (CCD)

(ii) Box- Behnken designs (BBD)

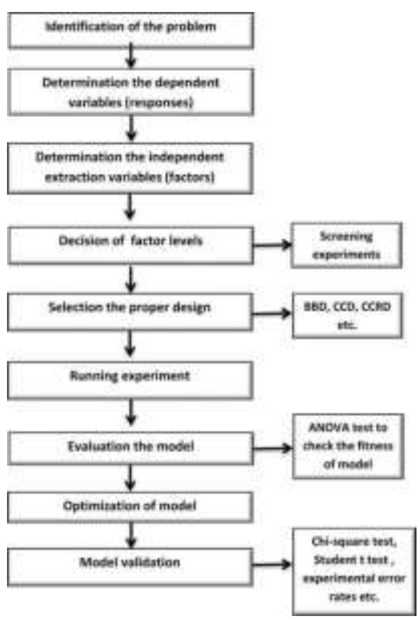

Figure 1: Steps for response surface methodology

In the model production system, RSM involves the use of statistical experimental technology design and the lowest squared appropriate approach. There is normally no established relation seen between output characteristic and the entrance variables. In general, a computational surface model for the second-order polynomial answer is used to evaluate parametric effects on different yield criteria. The second-order model enables developers to consider each factor's second-order impact independently and how these factors communicate in two directions.

This mathematical second-order model can be been seen as follows:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_{ii}^2 + \sum \sum_{i<j} \beta_{ij} X_i X_j + \varepsilon, \quad (1.1)$$

where Y is the comparing yield, $X_i$is the information factors, X_{ii} and X_iX_j is the squares and interaction terms of these information variables. The parameter of regression coefficients are β_0,β_i,β_{ij} and β_{ii} and the experimental error is ε(Tsao, 2008).

Polynomials are the most frequently used approaching functions. At first, a polynomial of the first order is used, and then a second polynomial could be utilized in the optimal field. Different authors examined the implementation of the surface response technique (Abbasi and Mahlooji, 2012).

The RSM method could be divided into six phases for optimization:

- ❖ Selection and potential responses of predictor factors.
- ❖ Choice of the technique for experimental design.
- ❖ Experimentation and findings obtained.
- ❖ Adjustment of the experimental data model equation.
- ❖ Achievement of answer graphs and model checks (ANOVA).
- ❖ Optimum conditions determination (Witek-Krowiak et al., 2014).

2.1. Artificial Neural Networks (ANNs)

Neural networks represent a broad variety of nonlinear flexible regression and discriminating structures, standard statistical designs, and complex variation frameworks. They are often made up of a huge amount of "neurons," that is to say, of basic computational components, static or dynamic, often inter-connected but mostly organized into layers.

Three big applications are artificial neural networks:

- ❖ As inspired by biological and intelligent immune tissue.
- ❖ As true active suspension processors or operators for applications such as robots implemented in hardware.
- ❖ Methods of data analysis.

Developing artificial neural networks was a simulation effort by incorporating numerous basic computational facts (neurons) into a highly interrelated structure in order to mimic biological immune networks and the hope that dynamic processes like "intelligence" would arise from self-organization or understanding. Many model NNs, for example, the linear generalization, the polynomial regression, the not parametric regression, and discrimination analysis, regression projective pursuit, principal component analysis, and the clustering algorithms, are similar or identical to common statistical methods, particularly if the focus lies in predicting complex phenomena instead of explanations. These NN models can be extremely helpful. A few NN models, such as counter-diffusion, vector studying, and self-organizing charts, are also available with no specific statistical equivalents but are important for information processing (Witek-Krowiak et al., 2014).

2.2. Objectives

- To identify optimum process parameters for optimal performance.
- To compare output capacity for RSM and ANN to statistical indicators likeR^2, RMSE and MSE.
- To identify the appropriate approach by comparison of yields by RSMS and ANNs techniques and provide guidance on more policymaking in the optimization process for more efficient technology.

3. Review of Literature

Qadir *et al.* (2018) targeted study was to show the physical and mechanical belongings of 100% yarn slub usually utilized in dungaree and further easygoing wear. Measurable methods were created utilizing focal complex trial plan of the reaction surface approach. Yarn's straight thickness, slub depth, slub size and interruption measurement were utilized as the fundamental facts factors although yarn forte, prolongation, number of mass variety, flaws and shagginess were utilized as reaction/yield factors. The situation was reasoned that yarn asset plus extension expanded by expansion happening direct thickness and interruption measurement, and diminished with expansion in slub wideness and slub size. It was additionally reasoned that because of genuinely critical square and association impacts of a portion of the information factors, just the quadratic model rather than the straight models can enough address the connection concerning the information and the yield factors.

Esonye *et al*. (2019) conducted a study which showed that the development of biofuel from Sweet almond essential oils (SASO) via trans-esterification of the Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) . Heat optimization levels (30 °C to 70 °C), intensity of the catalyst (0.5% rw/w to 2.5% rw/w), reaction period (45 – 65 min) and molar oil/methanol ratio (1:3 mol/mol to 1:7 mol/mol) were all the central composite design (CCD) conditions. Normal techniques were used to produce the physical characteristics of seed oil and the methyl ester. The fatty acids were measured by GC-MS by using technology of FT-IR. At the catalyst

Chouaibi et al. (2020) optimized the decreasing glucose concentrations and bio-ethanol production by pumpkin peeled scrap using two modeling approaches Artificial neural network (ANN) and Response surface methodology (RSM). It was found that a rotatable design maximized bioethanol production in order to maximize reducing sugar output. The hydrolysis period was 120 minutes, α-amylase concentration was 7.5 units per gramme, substrate loading was 17.5 grammes per liter, and amyl glucosidase concentration was 56.40 units per milliliter. The temperature of 45oC, pH of 5.06, shaking speed of 188.5 rpm, and yeast concentration of 1.95 g/L are the parameters for fermentation.

M-Ridha *et al.* (2020) studied E. coli and Bacillus sp. is used to remove the dyes Reactive Red 195 and Reactive Blue, Escherichia and Bacillus species by using the Design of Experiment (DOE) for two levels with five components Response surface methodology to study the effects of time and solution pH, initial dye concentration, bio mass loading and temperature on aqueous solution. There were checks for adequacy, P-values, F-values, and lack of fit on a quadratic polynomial equation, as well as later replication at the optimum value according to the desirability function by minimizing the number of experiments, quadratic approaches were utilized to optimize the operational settings. Researchers found that biodegradable dyes were significantly impacted by two different types of bacteria.

Tyagi *et al.* (2021) investigated by use of The Pin-On-Disc Test the wear behavior of manufactured composites at varied sliding lengths and varying applied loads. Response surface approach and artificial neural network (ANN) were compared to discover which model was more accurate at predicting the future (RSM). The RSM model was utilized to maximize the process parameter.

Modeling of composites created at 1200 tool rational speed with 20 N loads and at a 300m sliding distance anticipated different situations, two types of analysis were performed: (i) Scanning Electron Microscopy (ii) Energy Dispersive Spectroscopy. Analysis showed that Adhesive was main wear mechanism and presence of oxide layer on wear surface.

4. Materials and Methods

4.1. Data

Main input variables of Yarn's slub length, slub thickness,pause length and linear density although the output variables of yarn elongation, imperfection, strength, coefficient of mass variation and hairiness will be used for the analysis by using RSM and ANN.

4.2. Source

The data of research will be taken from the Department of Polymer Engineering, Faculty of Engineering and Technology, National Textile University, Faisalabad.

The following methods were used to achieve the purpose.

4.3. Response surface Methodology

According to Bradley (2007) prime purpose of RSM is the optimization of underlined Response output. RSM is used for the following properties i.e. developing, enhancing and optimizing the real response factor and it can be mathematically represented as

$$y = f(x_1, x_2) + \epsilon \qquad (3.1)$$

Where Y is the response of interest and depend on x_1 and x_2 independent variables and ϵ is experimental error which indicates the influence of countable error if any on response of interest.

So, the mentioned objectives of the study RSM may be accomplished by:

- To understand the structure of response surface.
- To find the area whereas, optimum occurs. The goal is to move efficiently and quickly along with the way for developing minimum and maximum responses, and then the responses are optimized.

RSM gives rise to following advantages:

- As a result, responses and control variables are linked.
- Predicts response values for a variety of control factors. There are optimal settings for control variables that will result in maximum activity within a certain experimental design

5. Response Surface Designed Method

According to (Oehler, 2000) relation of response variable y and independent variable are customarily known. Generally lowest order polynomial equation is utilized for illustration of surface of interested response. The polynomials are ordinarily adequate values in small amount of area of response surface. So, dependent on approximate form of not known function of 'f' any of both first degree and second-degree models are applied. Approximated value of function is the first-degree polynomial as response is linear function of independent.

5.1. Regression Model

Regression model contains the relationship of different variables named as controlled variables and uncontrolled variables known as response y obtained by mathematical model and multiple regression model is that model which contains more than one uncontrolled variable termed as independent. Generally, a regression with q independent variables is defined as per following form:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_q x_{iq} + \epsilon_i \qquad \text{(i= 1, 2, 3,…, N)} \qquad (3.2)$$

$$\mathrm{Y} = \beta_0 + + \sum_{i=1}^{n} \beta_j \, x_{ij} +$$

Where q < n is the parameter β_j quantifies expected modification in output variable y per component like in x_{ij} as the other than that independent variables are considering fixed. x_{ij} signify as i^{th} value and j^{th} level of the independent variable in equation (3.2) and (3.3).

5.2. Neural Networks

The neural network method has been used in almost every aspect of life, including pattern recognition, textile architecture, and assessment and verification systems, to solve complicated technical problems. In reality, neural networks are a type of non-linear regression. There are three main applications where neural networks are used. i.e firstly the nervous system or intellect with a biological reference, second principal purpose of ANN is to engender coherent intelligent of software and signal related to machine learning e.g robots and third main use of ANN is to analyze data.

5.3. Biological description of model

The description of significant features **of** physiology structure of neuron group for the phase for the construction of ANN model that do not be operated serially; when turning devices do. NN have categories in multi-layered hierarchical structure that has them away from cellular type devices. In ANN type of study each of them may associate with each other. In opposition to other computers, there no application of program is given to devices. That kind of application of program has to been developed i.e. the parameters termed as free/hyper parameters of method have to be devised adaptive in nature. The charm that still pervaded to researcher's threshold value, soma generates electrical signal which is moved to currently connected neurons.

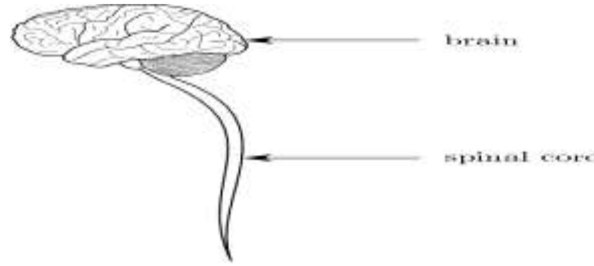

Figure 1: General view of central nervous system

5.4. The Axon

These electrical signals are moved to connected neurons. It is slim and long extended part of soma. Inside the spinal cord, it can be extended to meter in extreme case. The axon is electrically inaccessible for good formed electrical signal and it guides to dendrites to transfer signals to other connected neurons. This is the whole cycle of inside neuron function.

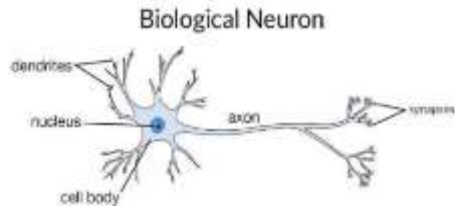

Figure 2: General structure of biological Neuron

5.5. Artificial Neural Network

Neural networks represent a broad variety of nonlinear flexible regression and discriminating structures, standard statistical designs, and complex variation frameworks. They are often made up of a huge amount of "neurons," that is to say, of basic computational components, static or dynamic, often inter-connected but mostly organized into layers.

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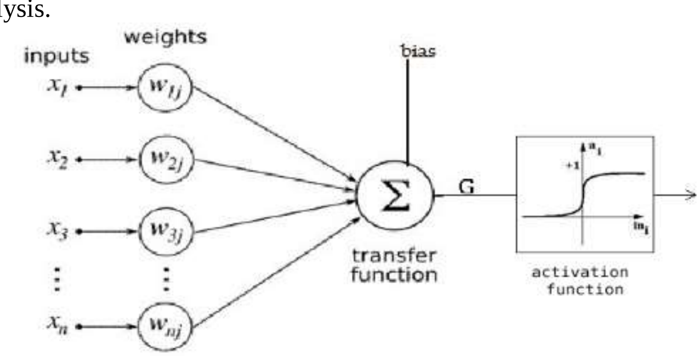


Figure 3: Neuron with activation function

5.6. Activation Function

A perception is calculated as linear combination of inputs is named as net input. For production of output a perhaps non-linear activation function is utilized. In general, an activation function is bounded with range between zero to 1 or -1 to 1. These activation functions are mostly name as squashing functions (Sarle, 1994). Mostly used activation function functions are as fellows

- ❖ Linear function;
  - o $actv(y) = y$
- ❖ Tan-hyperbolic function
  - o $actv(y) = \tanh(y)$
- ❖ Logistic:
  - o $actv(y) = (e^{-y} + 1)^{-1} = \frac{(1+\tanh\frac{y}{2})}{2}$
- ❖ Normal
  - o $actv(y) = Y^2$

6. Result and Discussion

6.1. Response Surface Methodology

This experimentation adapted central composite rotatable design (CCRD) was conducted using R-Studio 4.0.4 considering four factors, viz, slub length, slub thickness,pause length and linear densityfor multiples yield (elongation, imperfection, strength, coefficient of mass variation and hairiness). Thirty numbers of runs were taken into account by central composite rotatable design. The runs were partitioned into three categories This experimentation adapted central composite rotatable design (CCRD) was conducted using R-Studio 4.0.4 4 considering four factors, viz, slub length, slub thickness,pause length and linear densityfor multiples yield (elongation, imperfection, strength, coefficient of mass variation and hairiness). Thirty numbers of runs were taken into account by central composite rotatable design. The runs were partitioned into three categories

$$n_f = 16$$
$$n_\alpha = 8$$
$$n_c = 6$$

Data based on CCRD in order to optimize the process condition were utilized for determining the coefficients pertaining to regression equation of second – degree multiple regression models by means of following equation:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_{ii}^2 + \sum\sum_{i<j} \beta_{ij} X_i X_j + \epsilon_i \qquad (4.1)$$

ϵ_i is the residual.

Table 1: Estimation of Yarn Strength along significance values

Terms	Estimate	Std.Error	t-value	Pr(>|t|)
(Intercept)	951.83	44.52	21.38	0.00 *
X1 (Y.D)	12.17	22.26	0.55	0.59
X_2 (S.T)	-62.83	22.26	-2.82	0.01 *
X_3 (S.L)	-16.92	22.26	-0.76	0.46
X_4 (P.L)	54.50	22.26	2.45	0.03 *
$X_1 X_2$	90.38	27.26	3.31	0.00 *
$X_1 X_3$	-28.88	27.26	-1.06	0.31
$X_1 X_4$	29.13	27.26	1.07	0.30
$X_2 X_3$	-11.13	27.26	-0.41	0.69
$X_2 X_4$	9.63	27.26	0.35	0.73
$X_3 X_4$	-3.63	27.26	-0.13	0.90
X_1^2	22.58	20.82	1.08	0.30
X_2^2	2.83	20.82	0.14	0.89
X_3^2	20.96	20.82	1.01	0.33
X_4^2	-19.67	20.82	-0.94	0.36

$R^2$0.67Adjusted$R^2$0.38

$Y_1 = 951.83+12.17X_1-62.83X_2-16.92X_3+54.50X_4+90.38X_1\ X_2-28.88X_1\ X_3+29.13X_1\ X_4-11.13X_2X_3\ +9.63X_2\ X_4-3.63\ X_3\ X_4+22.58X_1^2+2.83X_2^2+20.96X_3^2- -19.67X_4^2$ (4.1)

In this model interaction factor intercept, X_2, X_2 and X_1X_2 are highly significant. Here R^2= 0.67model R^2 is equal to 67%. So, it is good for prediction of Yarn Strength. The individua parameters significance of the fitted model for response was obtained using by its pertinent in Table 2 the least P-value of the parameter, the greater the significance of the parameter, so the P-values report the relative significance of the individual pertinent to the specific parameter. Least P-values pertaining to the linear and quadratic terms of the yields proposed that the contribution of factors was significant in the model and R^2 indicates the 67% data fit the model.

Table 2: Analysis of Variance (ANOVA)

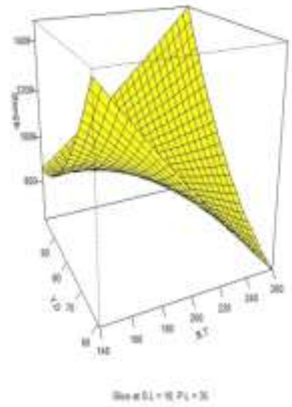
Source	Df	Sum Sq	Mean Sq.	F- value	Pr(>F)
FO	4	176460	44115	3.7092	0.02722
TWI	6	161268	26878	2.2599	0.09385
PQ	4	40727	10182	0.8561	0.5121
Residuals	15	178400	11893		
Lack of fit	10	178390	17839	8233.3654 6	7.40E-11
Pure error	5	11	2		

Table 4.5 shows the results in detail of ANOVA to fit the second- degree RSM model. 8233.365 for P-value for the lack of fit test suggest that lack of fit test has significant value. Lack of fit should be insignificant. But there it is only 0.00001% chances that lack of fit could occur on account of other. Furthermore, the chances are very low to occur

6.2. Predicted model equation

The above equation represents the predicted model of yarn strength for the variation of yarn linear density, slubthickness,slub length and pause length.

6.3. Predicted effects of Slub Parameters on Yarn Strength



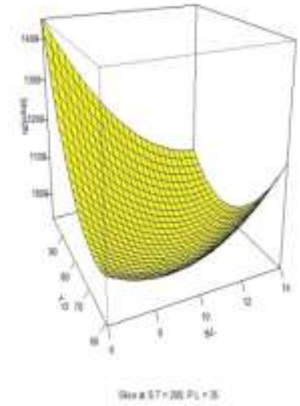


Figure4.1 yarn density vs. figure4.2 yarn density vs. Slub ThicknessSlub Length

Table 3: Estimation of Elongation along significance values

Terms	Estimate	Std. Error	t-value	Pr(>|t|)
Intercept	3.183	1.543	2.06	0.056
X1 (Y.D)	-0.257	0.221	-1.16	0.263
X_2 (S.T)	-1.073	0.067	-1.59	0.130
X_3 (S.L)	-2.869	0.947	-0.30	0.766
X_4 (P.L)	-1.623	0.119	-1.36	0.192
$X_1 X_2$	0.001	0.0005	2.25	0.039 *
$X_1 X_3$	-0.009	0.0077	-1.21	0.244
$X_1 X_4$	0.001	0.001	1.11	0.286
$X_2 X_3$	-0.0007	0.002	-0.03	0.977
$X_2 X_4$	0.00029	0.0003	0.93	0.366
$X_3 X_4$	0.0035	0.0046	0.75	0.464
$X_1{}^2$	0.0005	0.001	0.49	0.626
$X_2{}^2$	0.000005	0.0001	0.04	0.965
$X_3{}^2$	0.042	0.0263	1.59	0.133
$X_4{}^2$	-0.00003	0.0004	-0.07	0.941

$R^2$0.60Adjusted$R^2$0.37

In this model interaction factor X_1 and X_1X_2 are highly significant. Here R^2= 0.60 model R^2 is less than 67%. So, it is better for prediction of Yarn Strength. The individually parameters significance of the fitted model for response was obtained using by its pertinent in Table 4.6 the least P-value of the parameter, the greater the significance of the parameter, so the P-values report the relative significance of the individual pertinent to the specific parameter. Least P-values pertaining to the linear and quadratic terms of the yields proposed that the contribution of factors was significant in the model and R^2 indicates the 60% data fit the mode

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