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IMPROVEMENT USING AN ARTIFICIAL NEURAL NETWORK AND COMPARISON WITH RESPONSE SURFACE TECHNIQUE FOR YIELDING MULTIPLES

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ABSTRACT

Cotton slub yarn is frequently utilized in mechanical, physical, and casual conditions as well as denomination. The Department of Polymer Engineering at National Textile University in Faisalabad provided the data for the main objective. Analysis is done using software written in the R programming language. Cotton production is influenced by a number of variables, all of which have a direct impact on process efficiency. In order to maximize numerous yields (elongation, imperfection, strength, coefficient of mass variation, and hairiness), the study aimed to optimize the 100% cotton slub yarn model (slub length, slub thickness, pause length, and linear density).By evaluating a set of quality parameters, such as process efficiency, using two techniques—response-surface methodology (RSM) and artificial neural network (ANN)—and comparing the results using mean square error (MSE), optimization is a means of determining and improving the performance of the built framework. For added accuracy, the mean square error root (RMSE) and coefficients of determination () are employed. But in every category, the ANN has continuously outperformed the RSM. With an RMSE of 0.229, the final ANN model that was chosen was able to predict all five output parameters at once.

INTRODUCTION

One of the most important oleaginous and fiber crops is cotton, which accounts for 35% of global fiber production. Cotton is more significant to China since it is one of the country's most essential agricultural commodities. Cotton production is influenced by a number of variables, all of which have a direct impact on process efficiency. Therefore, for both prediction and improvement, an efficient numerical equation ought to be used. By evaluating a set of quality metrics, such process efficiency, optimization is a method of determining and improving the built framework's performance. The goal of improving the bio massing cycle is to determine the particular conditions (ecological and/or design aspects). Typically, experiments are conducted to apply and assess certain factors while leaving others unaffected (Wang *et al*., 2020).

Yarn

Fabric is the fundamental unit of textiles. Yarn is created by interlocking fabric. One may say that dovetailed cloth is yarn with a long, continuous length. Yarn is made in the textile industry using knitting, crocheting, sewing, weaving, and rope-making techniques.

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Slub Yarn

Yarn is defined as yarn that has spun with slubs. Slub yarn is intentionally designed to provide character to a garment. Yarn is a continuous, long-length interlocking fiber composed of both synthetic and natural fibers. One may even create Slub yarns. These yarns are sent to various locations by yarn makers worldwide.

Fabric

A type of material called fabric is created by weaving and mixing several threads. Sheets, clothing, and curtains are all made of fabric. Fabric is made with both natural and synthetic thread. Knitting, non-weaving, and weaving are the traditional techniques used to create cloth.

Woven fabric:

Weaving and combining several threads results in fabric, a form of material. Fabric is used to make curtains, clothes, and sheets. Both synthetic and natural thread are used to make fabric. Traditional methods for making fabric include knitting, non-weaving, and weaving.

- Plain
- Twill
- Stain

Fabric properties have:

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

Plain weave:

One of the most common weave is plain weave. Structure of plain wave by each weft yarn underneath and finished each warp yarn for knitting tenacity.

Twill:

As compare plain and stain weave twill weave has a design of diagonal comparable spine. In this weave arrangement, the weft thread passes terminate one or, more warp threads then under two or more warp threads and so on.

Stain:

Stain is kind of fabric which has silky surface and non-growly back. Stain is constructed by more than four weft yarns with a warp yarn and four warp yarns fluctuating over a solo weft yarn. Gyrated yarns are used to make sateen fabric.

Knitted Fabric:

Spongy fabric is processed to make elastic knitting. It is kin of fabric in which is used to inter wine yarn needles are used. To form loops two kinds of yarns are used. The vertical rows of loops are known as ribs, and the horizontal rows are known as courses.

Non- Woven Fabric:

Continues lengthy fiber and short fiber are used to made non-woven fabric. It has been bounded by heat, chemical and mechanical norms.

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.

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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.

Slub Yarn Nature

A yarn that is spun with the goal of completing an uneven form in both diameter and length is called a slub yarn. Slubbed cloth has historically been seen as inferior and flawed. Modern spinning machinery allows for the production of flawless, uniform, and smooth yarns. Slubs are a feature that contributes to the fabric's character rather than being a flaw or defect.

Methodology of Response Surfaces (RSM)

The goal of RSM, which is a collection of analytical tools, is to increase interest responses by creating procedures that maximize and enhance them. One of the greatest methods of the past 20 years is the Response Surface Technique. According to Bas and Boyacı (2007), it is useful for designing, developing, commercializing, and improving core product models. (Bezerra et al., 2008) suggested the empirical optimization strategies for RSM implementations. To attain the advantage, optimization is employed to maximize the efficiency of a technology, item, or function. The optimization technique is frequently employed in analytical chemistry to provide the best possible response. In RSM, statistical and mathematical abilities are used to empirically grounded models.

The theoretical work and its applications of RSM have been recognized for the purpose of implementing multivariate statistical methods. Second-order model fitting and analysis are only a small part of RSM. The RSM is well known and has played a significant role in industrial experimental work. 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 1.1 Steps for response surface methodology

RSM uses the lowest squared suitable strategy and statistical experimental technology design in the model manufacturing system. Typically, there is no discernible relationship between the input factors and the output characteristics. Parametric influences on various yield criteria are generally assessed using a computational surface model for the second-order polynomial solution. Developers may take into account the independent second-order effects of each element as well as the two-way communication between these factors thanks to the second-order model.

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 $X_i X_j$ 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).

Artificial Neural Networks (ANNs)

Standard statistical designs, sophisticated variation frameworks, and nonlinear adaptable regression and discriminating structures are all represented by neural networks. They are frequently composed of a vast number of "neurons," or fundamental computing elements, which can be either static or dynamic. These are frequently coupled to one another, but they are mostly arranged in 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.

In order to simulate biological immune networks and the expectation that dynamic processes like "intelligence" would emerge from self-organization or understanding, artificial neural networks were developed by combining many fundamental computational facts (neurons) into a highly interconnected structure. Many model NNs, such as principal component analysis, discrimination analysis, regression projective pursuit, polynomial regression, linear generalization, clustering algorithms, and not parametric regression, are comparable to or identical to standard statistical techniques, especially when the goal is to predict complex phenomena rather than provide explanations. These neural network models can be quite beneficial. A few NN models that are crucial for information processing but lack exact statistical counterparts include self-organizing charts, vector studying, and counter-diffusion (Witek-Krowiak et al., 2014).

Objectives:

- To determine the ideal process settings for peak efficiency.
- To evaluate RSM and ANN output capability against statistical measures such as R^2, RMSE, and MSE.

- To compare the outputs from RSMS and ANN approaches in order to determine the best course of action, and to offer recommendations for more legislation in the process of optimizing technology for greater efficiency.

CHAPTER 2

REVIEW OF LITRATUR

The purpose of Qadir et al. (2018) was to demonstrate the mechanical and physical characteristics of 100% yarn slub, which is typically used in dungarees and other casual clothing. The response surface approach's focused complicated trial design was used to develop quantifiable techniques. While yarn forte, prolongation, number of mass varieties, defects, and shagginess were used as reaction/yield elements, the key facts factors were the yarn's straight thickness, slub depth, slub size, and interruption measurement. It was assumed that the yarn asset plus extension increased with direct thickness and interruption measurement and decreased with slub wideness and slub size expansion.

According to a study by Esonye et al. (2019), biofuel may be produced from sweet almond essential oils (SASO) via trans-esterifying Response Surface Methodology (RSM) and Artificial Neural Networks (ANN). The central composite design (CCD) settings included heat optimization levels (30 °C to 70 °C), catalyst intensity (0.5% rw/w to 2.5% rw/w), reaction time (45 to 65 min), and molar oil/methanol ratio (1:3 mol/mol to 1:7 mol/mol). The physical properties of the methyl ester and seed oil were produced using standard methods. Using FT-IR technique, GC-MS analyzed the fatty acids. At the catalyst

Chouaibi et al. (2020) used two modeling techniques, artificial neural networks (ANN) and response surface methodology (RSM), to maximize the production of bio-ethanol from pumpkin peeled scrap and the reduction of glucose concentrations. In order to maximize reducing sugar output, it was discovered that a rotational design enhanced the generation of bioethanol. The concentration of amyl glucosidase was 56.40 units per milliliter, the hydrolysis duration was 120 minutes, the substrate loading was 17.5 grams per liter, and the α-amylase concentration was 7.5 units per gramme. The fermentation conditions include a temperature of 45 °C, a pH of 5.06, a shaking speed of 188.5 rpm, and a yeast concentration of 1.95 g/L.

Using the Design of Experiment (DOE) for two levels with five components, M-Ridha et al. (2020) investigated how E. coli and Bacillus species are utilized to remove the dyes Reactive Red 195 and Reactive Blue. Response surface approach is used to investigate how temperature, starting dye concentration, biomass loading, duration, and solution pH affect aqueous solutions. Quadratic approaches were used to optimize the operational settings, and checks were made for adequacy, P-values, F-values, and lack of fit on a quadratic polynomial equation. Later replication was also conducted at the optimal value based on the desirability function by minimizing the number of experiments.

Tyagi et al. (2021) used The Pin-On-Disc to study Examine how produced composites wear under various applied loads and sliding lengths. To find out which model was better at forecasting the future, the response surface method and artificial neural network (ANN) were compared (RSM). The process parameter was maximized using the RSM model. Two kinds of analyses were carried out in order to model composites made at 1200 tool rational speed with 20 N weights and at a 300 m sliding distance in anticipation of various scenarios: (i) Energy Dispersive Spectroscopy (ii) Scanning Electron Microscopy.

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MATERIALS AND METHODS

DATA

Yarn's slub length, slub thickness, pause length, and linear density are the primary input factors; however, RSM and ANN will be utilized to analyze the output variables of yarn elongation, imperfection, strength, coefficient of mass variation, and hairiness.

Source

The Department of Polymer Engineering, Faculty of Engineering and Technology, National Textile University, Faisalabad, will provide the research data. To accomplish the goal, the following techniques were employed

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
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

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.

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$\beta_j$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).

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NEURAL NETWORKS:

Neural networks have been utilized to address complex technological challenges in nearly every area of life, including textile architecture, pattern recognition, and evaluation and verification systems. Neural networks are actually a form of non-linear regression. Neural networks are utilized in three primary applications. For example, the first is the nervous system or intelligence with a biological reference; the second is the creation of coherent intelligent software and signals connected to machine learning, such as robots; and the third is the analysis of data.

FIRST-DEGREE MODEL DESIGN:

First- degree model is utilized to illustrate the regular surfaces either it is titled or not. The first degree equation approximating the function f has reasonably not too curvature check in region and that is not excessively large. First degree model is supposed to be reasonable approximating the right surface in smallest area of the x's (Montogomery, 2013).

A first degree equation with N experimental runs accomplishing by q designs variables and only single response can be represented as:

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

SECOND DEGREE RFESPONSE SURFACE ANALYSIS:

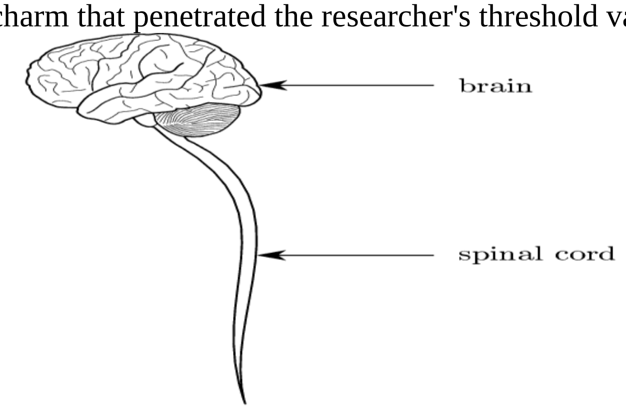
When there is curvature in surface then first degree model is not enough to analyze. A parabolic curvature for second degree model is fitted for approximation a region of right response surface. The second degree model is defined as:

$$\mathrm{Y} = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_{ii}^2 + \sum\sum_{i<j} \beta_{ij} X_i X_j + \epsilon_i \quad (3.5)$$

Second-degree model has flexibility on account of diversity of functional form and approximating in surface locally (Montogomery, 2013).

BIOLOGICAL DESCRIPTION OF MODEL:

Describing important aspects of the neuron group's physiology and structure for the ANN model-building phase that need serial operation, as opposed to turning devices. NNs are separated from cellular-type devices by their multi-layered hierarchical structure. Each of them may associate with the others in an ANN-type research. Unlike other computers, gadgets do not receive any software applications. This type of software application must be created, meaning that the parameters referred to as the methods free or hyper parameters must be adaptively designed. The soma produces an electrical signal that is sent to the neurons that are now attached, retaining the charm that penetrated the researcher's threshold value.



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General view of central nervous system

THE AXON:

Neurons that are linked receive these electrical impulses. It is a long, slender portion of the soma. In severe cases, it can be stretched to a meter within the spinal cord. For a well-formed electrical signal, the axon is electrically inaccessible. It then travels to dendrites to transmit messages to other neurons that are attached to it. This is the entire cycle of neuronal activity.

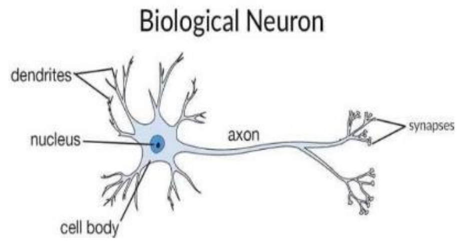

Figure 3.2 General structure of biological Neuron

Artificial Neural Network

Standard statistical designs, sophisticated variation frameworks, and nonlinear adaptable regression and discriminating structures are all represented by neural networks. They are frequently composed of a vast number of "neurons," or fundamental computing elements, which can be either static or dynamic. These are frequently coupled to one another, but they are mostly arranged in layers. Artificial neural networks have three major applications:

- ❖ 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.

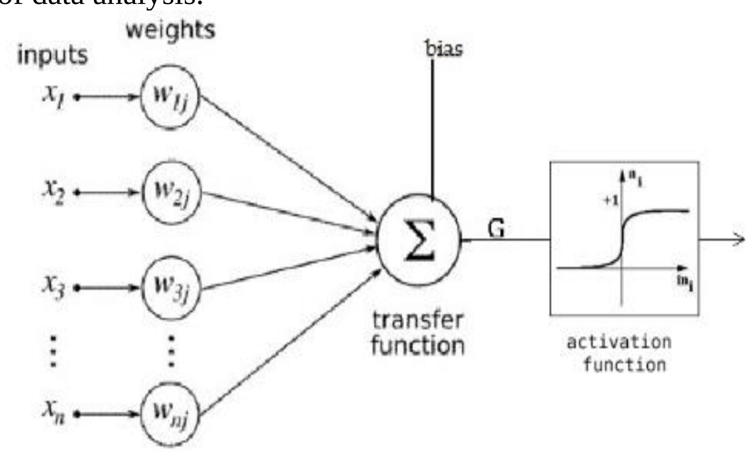

Figure 3.3 Neuron with activation function

ACTIVATION FUNCTION:

A perception is computed as a net input, which is a linear mixture of inputs. A possibly non-linear activation function is used to produce the result. An activation function is often restricted by a range of -1 to 1 or 0 to 1. According to Sarle (1994), these activation functions are

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commonly referred to as squashing functions. Fellows are the most frequently utilized activation function functions.

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

RESULT AND DISCUSSION

RESPONSE SURFACE METHDOLOGY:

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:

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

ϵ_i is the residual.

Table 4.4 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

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$X_3 X_4$	-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

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

In this model interaction factor intercept, X_2, X_2 and X_1X_2 are highly significant. Here R^2= 0.67 model R^2 is equal to 67%. So, it is good for prediction of Yarn Strength. The individua paramet ers significance of the fitted model for response was obtained using by its pertinent in Table 4.4 the least P-value of the parameter, the greater the significance of the parameter, so the P-values r eport 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 4.5 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

Predicted model equation:

The above equation represents the predicted model of yarn strength for the variation of yarn linea r density, slub thickness, slub length and pause length.

Predicted effects of Slub Parameters on Yarn Strength

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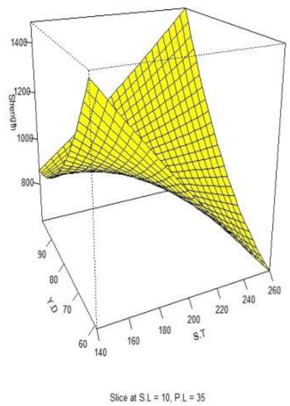

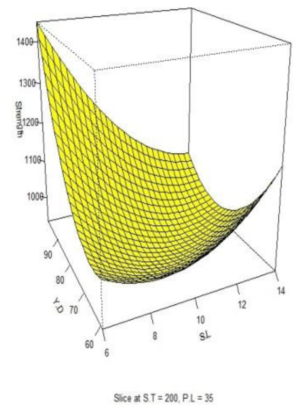

Figure4.1 yarn density vs. figure4.2 yarn density vs. Slub Thickness Slub Length

Table 4.6 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 rep ort the relative significance of the individual pertinent to the specific parameter. Least P-v alues pertaining to the linear and quadratic terms of the yields proposed that the contribution of f actors was significant in the model and R^2 indicates the 60% data fit the mode

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