Research Article

Performance Optimization, Prediction, and Adequacy by Response Surfaces Methodology with Allusion to DRF Technique

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The RSM introduces statistically designed experiments for the purpose of making inferences from data. The second-order model is the most frequently used approximating polynomial model in RSM. The most common designs for the second-order model are the $3k$ factorial, Doehlert, Box-Behnken, and CCD. In this Box and Behnken design of three variables is selected as a representative of RSM and 70 : 30 polyester-wool DRF yarn knitted fabrics samples as a process representative. The survey reveals that second-order model is the most frequently used approximating polynomial model in RSM. The Box-Behnken is the most suited design for optimization and prediction of data in textile manufacturing and this model is well-suited for DRF technique yarn knitted fabric. The trend was as higher wool fiber length shows higher fabric weight, abrasion, and bursting strength, correlation of TM was not visible; however, role of strands spacing is found dominant in comparison to other variables; at 14 mm spacing it shows optimum behaviors. The optimum values were weight (gms/m²) 206 at length 75 mm, TM 2.5 and 14 mm spacing, abrasion (cycles) 1325 at length 70 mm, TM 2.25 and 14 mm spacing, bursting (kg/cm²) 14.35 at length 70 mm, and TM 2.00 and 18 mm spacing. A selected variables, fiber length, TM, and strand spacing, have substantial influence. The adequacies of response surface equations are very high. The line trends of knitted fabric basic characteristics were almost the same for actual and predicted models. The difference (%) was in range of 1.21 to -1.45, 2.01 to -7.26, and 17.84 to -6.61, the accuracy (%) was in range of 101.45 to 98.79, 107.27 to 97.99, and 106.61 to 82.16, and the Discrepancy Factor (R -Factor) was noted to be 0.016, 0.002, and 0.229 for weight, abrasion, and bursting, respectively, between actual and predicted data. The L -estimation factors for actual and predicted data were that (i) the ratio were in range of 1.01 to 0.99, 1.02 to 0.93, and 1.22 to 0.94 for weight, abrasion, and bursting, respectively, (ii) the multiple-ratio was in range of 1.26 to 0.86, (iii) the ratio product was in range of 1.22 to 0.92, and (iv) the totting ratio was in range of 1.02 to 0.94.

1. Introduction

The response surface methodology (RSM) introduces statistically designed experiments for the purpose of making inferences from data. To achieve this goal, statistical considerations for preliminary planning of experiments, standard statistical designs for experiments, and underlying logic for using these designs are emphasized. It is a common but major error to view statistics as a tool to be used only after the experiments are completed. Even using their most sophisticated tools, researchers receiving data from improperly designed experiments can make only indistinct and approximate inferences. Therefore, it is unfortunate, because

experimental data represent an expenditure of both time and money [1].

In general, the theoretical model that relates some controllable variables to a response either is not available or is very complex. Identifying and fitting from experimental data an appropriate response surface model requires some use of statistical experimental design fundamentals, regression modeling techniques, and optimization methods. As an important subject in the statistical design of experiments, RSM, introduced by Box and Wilson [2], comprises a group of mathematical and statistical techniques that is useful for empirical model building and analysis of problems in which a response of interest is influenced by several variables [3].

It is important to fit a mathematical model equation in order to approximate a relationship between response and independent variables and determine the optimum settings of these variables that result in the maximum response.

The two important models that are commonly used in RSM, including the first-order model and second-order model [4], are as follows:

$$Y = \beta_0 \sum_{i=1}^k \beta_i X_i + \varepsilon, \quad (1)$$

$$Y = \beta_0 \sum_{i=1}^k \beta_i X_i + \sum_{i=1}^k \beta_{ii} X_i^2 + \sum_{i=1}^k \sum_{i \neq j=1}^k \beta_{ij} X_i X_j + \varepsilon, \quad (2)$$

where Y is the response, β_0 is the constant, β_i is the slope or linear effect of the factor X_i , β_{ii} is the quadratic effect of the factor X_i , β_{ij} is the interaction effect between the input factors X_i and X_j , and ε is the residual term. The first-order models are inadequate to represent true functional relationships with independent variables. The second-order model is most suitable, highly structured, flexible, and diversified in order to locate the optimum point.

1.1. Designs for Fitting the Second-Order Model. The second-order model is the most frequently used approximating polynomial model in RSM. The most common designs for the second-order model are the $3k$ factorial, Doehlert, Box-Behnken, and central composite designs (CCDs) [5, 6]. These symmetrical designs differ from one another with respect to their selection of experimental points, number of levels for variables, and number of runs and blocks.

1.2. $3k$ Factorial Design. The $3k$ factorial design consists of all the combinations of the levels of the control variables with three levels each: low, medium or centre, and high [4]. The number of experimental runs (N) required for this design is defined as $N = 3k$, where k is the number of factors. The $3k$ factorial design needs a large number of experimental runs for large k , which loses its efficiency in the modeling of quadratic functions. Therefore, a $3k$ factorial design is more appropriate having factors numbering less than five. Due to its requirement for more experimental runs it can usually be accommodated in practice; designs that present a smaller number of experimental points, such as Doehlert, Box-Behnken, and CCDs, are more often used. The application of $3k$ factorial design is not frequent, and the use of this design has been limited to the optimization of two variables, because its efficiency is very low for a higher number of variables.

1.3. Doehlert Design. The Doehlert (or uniform shell) design has been developed by Doehlert [7]. The Doehlert design is for heterogeneous levels of variables. This property is important when some variables are subject to restrictions, such as cost and/or instrumental constraints, or when it is important to study a variable at major or minor levels. The intervals between each variable level must have a uniform distribution [6]. The number of experiments required (N) for

the Doehlert design is defined as $N = k_2 + k + C_0$, where k is the number of factors and C_0 is the number of centre points. For two variables, a central point surrounded by six points from a regular hexagon represents this design. For three variables, it is represented by a geometrical solid called a cub octahedron, and depending on how this solid is projected in the plane, it can generate some different experimental matrices. Although its matrices are neither orthogonal nor rotatable, it presents some advantages, such as requiring few experimental points for its application and high efficiency [8].

1.4. Box-Behnken Design. This design was developed by Box and Behnken [9]. The Box-Behnken design provides three levels ($-1, 0, +1$) for each variable, which are equally spaced. The number of experiments required (N) is given by $N = 2k(k-1) + C_0$, where k is the number of variables and C_0 is the number of central points. The design is represented as a cube and all points lie on a sphere of radius $\sqrt{2}$. In addition, this design does not contain any points at the vertices of the cubic region created by the upper and lower limits for each variable [10]. The Box-Behnken design for three variables takes optimization with its 13 experimental points. This design is more economical and efficient in terms of the number of required runs than their corresponding $3k$ designs with 27 experiments. Therefore, this design is useful in avoiding experiments that would be performed under extreme conditions, for which unsatisfactory results might occur. However, it is ineffective for situations in which we would like to know the responses at extremes.

The Box-Behnken design has been used for finding the optimum experimental conditions, leading to an optimal efficiency of different processes.

1.5. Central Composite Design. The CCD presented by Box and Wilson in 1951 [2] is the design most commonly used for fitting second-order models and it has been subjected to much attention in the theoretical development of its properties as in its practical use [10]. This design combines a two-level full or fractional factorial design with additional start points and at least one point at the centre of the experimental region. The CCD is widely used for the optimization of three variables. This design requires an experiment number according to $N = 2k + 2k + C_0$, where k is the number of factors and C_0 is the number of central points. In CCD, all factors are studied in five levels. This N experiment is distributed as follows [4, 10].

- (1) Full (or fractional) $2k$ factorial experiments, whose factors levels are coded as $-1, +1$: these experiments are the only points that contribute to the estimation of the two-factor interactions.
- (2) Axial (or star) $2k$ experiments with coordinates $(\pm\alpha, 0, \dots, 0), (0, \pm\alpha, \dots, 0), \dots, (0, 0, \dots, \pm\alpha)$: the codified value of α is defined as $\alpha = (2k)^{1/4}$. The axial points do not contribute to the estimation of interaction terms. If curvature is found in the system, the addition of axial points allows for efficient estimation of the pure quadratic terms.

- (3) C_0 central points at $(0, 0, \dots, 0)$: these experiments provide an estimation of pure error and contribute to the estimation of quadratic terms. The CCD is a rotatable and orthogonal design. A design is rotatable if the precision of the response estimation in all directions is equal and the orthogonality of the design means that different variable effects can be estimated independently. This design has been widely used for the optimization of several processes [11].

1.6. Optimization by Response Surface Methodology. In most production processes, the theoretical model that relates some controllable variables (factors) to a response either is not available or is very complex. In conventional methods used to determine this relationship, experiments are carried out varying systematically the studied parameter and keeping the others constant. This should be repeated for all the influencing parameters, resulting in an unreliable number of experiments. In addition, this exhaustive procedure is not able to find the combined effect of the effective parameters. In this way, the information about the relation between factors and response should be obtained in an empirical way [10, 12]. Using RSM, it is possible to estimate linear, interaction, and quadratic effects of the factors and to provide a prediction model for the response [13].

The textile industry is one of the largest and oldest industries worldwide and yarn manufacturing is the key process of it. The efficiency of yarn manufacturing depends on a number of factors, which are governed by the performance of fiber, yarn, and fabric initial characteristics and processing parameters of the experimental setup and also multiple pathways. Due to the complexity and variety of influencing factors, it is difficult to evaluate the relative significance of several affecting factors, especially in the presence of complex interactions [14]. In the day by day innovations and introduction of latest technologies in yarn and fabric manufacturing, large numbers of textile scientists are developing so many advances. The development of double roving feed (DRF) techniques is one of them and widely accepted by the textile producers. The DRF yarn uses are increasing in the entire field including the knit-wears.

In the recent studies, only traditional one-factor-at-a-time experiments were tested for evaluating the influence of operating factors on the DRF technique efficiency; however, very few researchers also used RSM. The DRF technique is not only time and work demanding but also completely lacks representation of the effect of interaction between different variables or factors. RSM allows an appropriate design of the experiments, which helps to decrease the number of runs. In addition, the modeling of the system facilitates the interpretation of multivariate phenomena and is valuable tool for scaling up [15].

The present endeavors reviewed the RSM techniques used for process optimization. The Box and Behnken design of three variables is selected as a representative of RSM. The DRF yarn knitted fabric production is chosen as a process for which the adequacy of the RSM is evaluated.

2. Material and Methods

2.1. Materials. The fibers specifications are given in Table 1.

2.2. Methods

2.2.1. Sample Preparation and Sequence of Operations. The sequence of operations for production of yarns and fabrics samples was as follows:

- (1) blending of polyester and wool in 70 : 30 (five passages in gill boxes) by weight;
- (2) combing (French combing);
- (3) gilling (three passages in gill boxes);
- (4) top formation;
- (5) gilling (four passages in gill boxes);
- (6) roving formation (simplex frame);
- (7) DRF yarn production (modified ring frame);
- (8) fabric production (knitted).

2.2.2. Attachments to Produce DRF Yarn. The following attachments are fitted in the conventional ring frame for the production of yarns by DRF technique:

- (1) rear roving guide;
- (2) double roving feeding attachments in drafting zone.

2.2.3. Spinning Parameters. The finisher sliver was processed in aforesaid sequence of operations to produce 24^s worsted count yarn at blend ratio 70 : 30 polyester wools by the following roving parameters:

- (1) roving wrapping: 0.50 grams per meter;
- (2) delivery speed: 45 meters per minute;
- (3) roving T.P.M.: 24.00;
- (4) roving C.V. (%): 6.10.

2.2.4. Knitted Fabric Production Details. Knitted fabric production details are as follows:

- (a) machine details:
 - (1) knitting machine: Black Burn, UK;
 - (2) feeder: 8 (two yarns per feed);
 - (3) gauge: 10 Needles/inch;
 - (4) speed (rpm): 22;
- (b) particular of fabrics:
 - (1) design: single jersey plain knit;
 - (2) yarn tension (gram/tex): 1.70;
 - (3) tube diameter (inches): 19.00.

TABLE 1: Fiber specifications.

Fiber used		64 ^s Australian Merino wool			Long staple (varying cut length) polyester
		1	2	3	
1	Longest (mm) staple length	160	165	170	150
2	Uniform (mm) staple length	115	119	124	130
3	Average (mm) staple length	65	70	75	89
4	Shortest (mm) staple length	15	15	15	35
5	Average micron (μ)	22.5	22.5	22.5	—
6	Moisture regain (%)	16.3	16.3	16.3	—
7	Bundle strength (gram/Tex)	12	12	12	14.4
8	Residual grease (%)	0.5	0.5	0.5	—
9	Alkali solubility	10.5	10.5	10.5	—
10	Urea bisulphite solubility (%)	42	42	42	—
11	Fineness (denier)	—	—	—	2.5

TABLE 2: Actual and coded values for independent variables and experimental design.

Sample code	X ₁ Wool fibre length (mm)		X ₂ Twist multiplier		X ₃ Strand spacing (mm)	
	Coded	Actual	Coded	Actual	Coded	Actual
1	−1	65	−1	2.00	0	14
2	1	75	−1	2.00	0	14
3	−1	65	1	2.50	0	14
4	+1	75	1	2.50	0	14
5	0	70	0	2.25	0	14
6	−1	65	0	2.25	−1	10
7	+1	75	0	2.25	−1	10
8	−1	65	0	2.25	+1	18
9	+1	75	0	2.25	+1	18
10	0	70	0	2.25	0	14
11	0	70	−1	2.00	−1	10
12	0	70	1	2.50	−1	10
13	0	70	−1	2.00	+1	18
14	0	70	+1	2.50	+1	18
15	0	70	0	2.25	0	14

2.2.5. Experimental Design. To study the individual and interactive effects of variables Box and Behnken factorial design was used for three variables. The following parameters are selected as prototype variables:

- (1) fiber length (X_1);
- (2) twist multiplier (X_2);
- (3) strand spacing (X_3).

Table 2 shows the coded and actual values of three parameters considered and fifteen sets of experimental combinations by DRF yarn and fabrics are knitted.

2.2.6. Measurement of Fabric Properties. There are numbers of fabric properties that can be optimized by using this experimental approach; however, three fundamental properties are

measured. The fabric weight per square meter (gms/mt²) (weight) was evaluated by ASTM D-3776-79 method taking 10 × 10 cm sample from different places of knitted fabric. The abrasion cycle (abrasion) was measured by ASTM D-1966 method using martindale abrasion tester. The specimens were mounted on rectangular blocks of 1.5 × 2.5 inches with abrading material, which was itself fabric and then a number of rubs were counted by noting the number of cycles from counter in abrasion cycles. The bursting strength (bursting) is determined by ASTM D-3886-80 method using diaphragm type tester operated by hydrostatic pressure. The fabric samples are clamped by means of metal rings of internal diameter 30 ± 5 mm in the tester, by screwing the clamping ring too tight over the test piece. Thus, pressure was increased on the diaphragm until the test piece burst in between 7 and 20 seconds to increase pressure from zero to bursting point and then readings were noted from the dial.

2.2.7. Development of Statistical Model. To correlate the effects of variables and the response, the following second-order standard polynomial was considered [16]:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 + b_{12}X_1X_2 + b_{13}X_1X_3 + b_{23}X_2X_3, \dots, \quad (3)$$

where Y represents the responses and $b_0, b_1, b_2, \dots, b_{23}$ are the coefficients of the model. The coefficients of main and interaction effects were determined by using the standard method. The response surface equations are calculated for prediction of responses.

2.2.8. Optimization of Fabric Properties. The optimum fabric performance was predicted by using equations at all levels of variables drawing contours.

2.2.9. Adequacy of Models. The followings terms were studied for the adequacies of the models.

- (a) Difference (%) is calculated by using the following equation:

$$\text{Difference (\%)} = \frac{(\text{Predicted Value} - \text{Actual Value}) \times 100}{\text{Actual Value}}. \quad (4)$$

- (b) Accuracy (%) is calculated by using the following equation:

$$\text{Accuracy (\%)} = \frac{\text{Actual Value} \times 100}{\text{Predicted Value}}. \quad (5)$$

- (c) Discrepancy Factor (R-Factor) is calculated [17] by using the following equation:

$$R = \sqrt{\frac{(\sum P_a - P_p)^2}{\sum (P_a)^2}}, \quad (6)$$

where R = Discrepancy Factor, P_a = actual values, and P_p = predicted values.

- (d) L-estimation is calculated by using the following equation:

$$\text{Ratio} = \frac{\text{Actual Value}}{\text{Predicted Value}}, \quad (7)$$

$$\text{Multiple Ratio} = R_1 \times R_2 \times R_3 \dots,$$

where $R_1, R_2, R_3, \dots$ are ratios of parameters 1, 2, 3, ... and we have

$$\begin{aligned} \text{Ratio Product} &= \frac{A_1 \times A_2 \times A_3 \times \dots}{P_1 \times P_2 \times P_3 \times \dots}, \\ \text{Toting Ratio} &= \frac{A_1 + A_2 + A_3 + \dots}{P_1 + P_2 + P_3 + \dots}, \end{aligned} \quad (8)$$

where $A_1, A_2, A_3, \dots$ are actual performances of parameters 1, 2, 3, ..., $P_1, P_2, P_3, \dots$ are predicted performances of parameters 1, 2, 3, ...

3. Results and Discussions

The actual observations, predicted values, and different calculated parameters for adequacy, response surface equations, and coefficient of correlation values are given in Table 3. The respective contours at different levels of variables were constructed and are given in Figures 1(a) to 1(c). The discussions are as follows.

3.1. Weight at Different Levels of Variables. From Figure 1(a), as depicted in (1)(A), TM decreases from 2.25 and spacing increases as the weight reduces. The trend is miscellaneous. (B) The trend is miscellaneous; TM and spacing increase as the weight decreases consistently. (C) Up to 14 mm spacing, as TM decreases from 2.25 weight decreases; however, at slightly above 2.25 TM, spacing increases as the weight also increases.

As depicted in (2)(A), two trends were found: first increasing weight as spacing increases in fiber length above coded level + 0.5 and second decreasing weight as length decreases from 70 mm. (B) As length decreases from 70 mm and spacing increases to 18 mm weight decreases. In length above 70 mm as spacing increases, weight increases and below reverse trend is visible. (C) In 70 to 75 mm in length as spacing increases, weight is reduced; however, when length is from 65 to 70 mm weight increases.

As depicted in (3)(A): TM decreases and length increases up to 70 mm, while weight decreases; however, in further increases in length weight increases. (B) As TM decreases and length is up to 70 mm weight decreases; however, in further increases in length weight increases. (C) Optimums were found at TM 2.25 and fiber length 70 mm.

3.2. Abrasion at Different Levels of Variables. From Figure 1(b), as depicted in (1)(A), the trends were miscellaneous as at TM up to 2.25 and spacing near 14 mm the optimum is seen. (B) As TM and spacing increase the abrasion cycles are reduced to a certain limit. At TM and spacing levels 0 the optimum is found. (C) The trend was almost similar to (B).

As depicted in (2)(A), as length and spacing increase abrasion increases. The abrasion cycles are lowest at low fiber length. All parallel lines show similar trends in all spacings. (B) The parallel horizontal lines show that optimum could not be found in the range and the fiber length increases at all spacings as abrasion increases. (C) The trend is almost similar to (A) as length decreases and spacing increases from the decrease of the abrasion cycles. All lines are parallel and showing the same relationship at each spacing and length.

As depicted in (3)(A), as TM increases and length decreases the tendency of reduction in abrasion cycles is noted. (B) As length decreases and TM is below 2.25, the abrasion reduces. After TM is 2.25 as length increases, abrasion decreases. (C) As the length decreases, TM increases, and abrasion reduces, the trend is miscellaneous.

3.3. Bursting at Different Levels of Variables. From Figure 1(c), as depicted in (1)(A), as spacing and TM increase up to a certain TM bursting increases. (B) As TM increases and

TABLE 3: Comparison of actual and predicted values.

Ref no.	(a)										(b)									
	Weight per square meter					Abrasion cycles					Bursting strength (kg/cm ²)					L-estimation				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	6	7	8	9	10
1	201	203.50	-1.24	101.24	0.99	1170.00	1233.54	-5.43	105.43	0.95	12.00	11.74	2.17	97.83	1.02	0.96	0.96	1383.00	1448.78	0.95
2	192	194.00	-1.04	101.04	0.99	1230.00	1233.54	-0.29	100.29	1.00	13.00	12.80	1.54	98.46	1.02	1.00	1.00	1435.00	1440.34	1.00
3	196	194.00	1.02	98.98	1.01	1200.00	1233.54	-2.80	102.80	0.97	12.10	12.90	-6.61	106.61	0.94	0.92	0.92	1408.10	1440.44	0.98
4	206	203.50	1.21	98.79	1.01	1150.00	1233.54	-7.26	107.26	0.93	13.05	12.56	3.75	96.25	1.04	0.98	0.98	1369.05	1449.60	0.94
5	186	186.33	-0.18	100.18	1.00	1270.00	1298.33	-2.23	102.23	0.98	13.20	12.50	5.30	94.70	1.06	1.03	1.03	1469.20	1497.16	0.98
6	197	195.79	0.61	99.39	1.01	1195.00	1281.45	-7.23	107.23	0.93	12.20	11.38	6.72	93.28	1.07	1.01	1.01	1404.20	1488.62	0.94
7	193	195.79	-1.45	101.45	0.99	1220.00	1281.45	-5.04	105.04	0.95	13.50	11.74	13.04	86.96	1.15	1.08	1.08	1426.50	1488.98	0.96
8	189	191.29	-1.21	101.21	0.99	1260.00	1315.21	-4.38	104.38	0.96	14.00	11.84	15.43	84.57	1.18	1.12	1.12	1463.00	1518.34	0.96
9	190	191.29	-0.68	100.68	0.99	1240.00	1315.21	-6.07	106.07	0.94	12.85	12.20	5.06	94.94	1.05	0.99	0.99	1442.85	1518.70	0.95
10	188	186.33	0.89	99.11	1.01	1325.00	1298.33	2.01	97.99	1.02	13.05	12.50	4.21	95.79	1.04	1.07	1.07	1526.05	1497.16	1.02
11	197	198.54	-0.78	100.78	0.99	1190.00	1169.16	1.75	98.25	1.02	12.20	11.33	7.13	92.87	1.08	1.09	1.09	1399.20	1379.03	1.01
12	187	189.04	-1.09	101.09	0.99	1280.00	1264.16	1.24	98.76	1.01	14.05	11.79	16.09	83.91	1.19	1.19	1.19	1481.05	1464.99	1.01
13	184	184.54	-0.29	100.29	1.00	1310.00	1297.92	0.92	99.08	1.01	14.35	11.79	17.84	82.16	1.22	1.22	1.22	1508.35	1494.25	1.01
14	193	194.04	-0.54	100.54	0.99	1210.00	1202.92	0.59	99.41	1.01	13.70	12.25	10.58	89.42	1.12	1.12	1.12	1416.70	1409.21	1.01
15	185	186.33	-0.72	100.72	0.99	1300.00	1298.33	0.13	99.87	1.00	13.10	12.50	4.58	95.42	1.05	1.04	1.04	1498.10	1497.16	1.00
Average	192.27	192.95	-0.37	100.37	1.00	1236.67	1263.78	-2.27	102.27	0.98	13.09	12.12	7.12	92.88	1.08	1.06	1.05			0.98
Max	206	203.50	1.21	101.45	1.01	1325	1315.21	2.01	107.27	1.02	14.35	12.90	17.84	106.61	1.22	1.22	1.26			1.02
Min	184	184.54	-1.45	98.79	0.99	1150	1169.16	-7.26	97.99	0.93	12.00	11.33	-6.61	82.16	0.94	0.92	0.86			0.94
R-Factor			0.016				0.002						0.229							

Response surface equations		(R ²)
1	$Y_{(\text{weight})} = 186.33 - 2.25X_3 + 7.21X_1^2 + 5.21X_2^2 + 4.75X_1X_2 + 4.75X_2X_3$	0.96
2	$Y_{(\text{Abrasion})} = 1298.33 + 16.88X_3 - 64.79X_2^2 - 27.50X_1X_2 - 47.50X_2X_3$	0.71
3	$Y_{(\text{Bursting})} = 12.50 + 0.18X_1 + 0.23X_2 + 0.23X_3 - 0.71X_3^2 - 0.35X_1X_2$	0.86

1: actual value; 2: predicted value; 3: difference (%); 4: accuracy (%); 5: actual values/predicted values; 6: product of 1 (all parameters)/product of 2 (all parameters); 7: product of 5 (all parameters); 8: sum of all actual values of parameters; 9: sum of all predicted values of parameters; 10: product (8*9).

(1) Weight at fiber length (mm) (A) 65, (B) 70, and (C) 75

(2) Weight at TM (A) 2.00, (B) 2.25, and (C) 2.50

(3) Weight at spacing (mm) (A) 10, (B) 14, and (C) 18

(a) Weight at different levels of variables

FIGURE 1: Continued.

(1) Abrasion at fiber length (mm) (A) 65, (B) 70, and (C) 75

(2) Abrasion at TM (A) 2.00, (B) 2.25, and (C) 2.50

(3) Abrasion at spacing (mm) (A) 10, (B) 14, and (C) 18

(b) Abrasion at different levels of variables

FIGURE 1: Continued.

(1) Bursting at fiber length (mm) (A) 65, (B) 70, and (C) 75

(2) Bursting at TM (A) 2.00, (B) 2.25, and (C) 2.50

(3) Bursting at spacing (mm) (A) 10, (B) 14, and (C) 18

(c) Bursting at different levels of variables

FIGURE 1: Fabric performances.

spacing decreases at a certain point bursting is optimum. Then, with further increase in TM and decrease in spacing, bursting decreased. (C) As TM from 2.25 and spacing from 14 mm increase bursting increases.

As depicted in (2)(A), as spacing increases below 70 mm in length decreasing trend is observed; however, at above 14 mm spacing trend was reversed. (B) As length and spacing increase the bursting decreases up to 70 mm in length. (C) The miscellaneous trends were noted after 70 mm of length and spacing increased; the bursting increases also as length increases, while from 70 mm as spacing increases bursting decreases.

As depicted in (3)(A), as TM decreases and fiber length increases up to 70 mm bursting decreases; however, from 70 to 75 mm of length as TM decreases from 2.25 to 2.50 bursting also decreases. (B) As TM decreases up to 2.25 and fiber length increases up to 70 mm bursting increases and with further decreases in TM bursting decreases. (C) As length increases and TM decreases bursting increases first up to a certain length then it decreases.

The fabric performance is proportional to the characteristics of fiber, yarn, and knit structures. In the study selected variables mainly have an impact on yarns and yarns are associated with knitted fabric.

In DRF spinning as fiber length increases more length traps in drafting results, a more compact yarn. At optimum TM, the emerging fibers from front roller nip are trapped at higher binding force and gain better packing density because the packing density weight per unit length of yarn is higher.

In higher spacing, convergence angle is greater, which generates higher false twist as strand results in more compact trapping of surface fibers and ultimately more compact yarn structure. In DRF production after optimum TM, there is comparatively loosely packed yarn which shows less weight per unit length of fabric. Also after or before optimum spacing between strands, the trapping of fiber reduces causing loose structure of yarn and ultimately as fiber length increases the weight of fabric decreases, also the abrasion and bursting strength are reduced. With the increase of TM and strand spacing up to a certain limit (optimum condition of spinning), weight, abrasion, and bursting strength increase; however, after or before optimum condition adverse behaviors are seen. The probable reason may be that, up to a certain limit, it helps in better insertion of twist in single strand which causes better trapping of fibers in the yarn periphery and thereby improvement in various properties of yarn and respective fabrics.

In other studies, almost similar findings were reported by Ghasemi and other workers that wool/polyester blended worsted yarn is successfully produced by feeding two roving in spinning system and that yarns' specifications such as tensile strength, elongation, and abrasion resistance remain almost unchanged [18].

The literature reveals that as fiber length, TM, or strand spacing reaches the optimum value, the yarns produced are more compact due to better binding. The numbers of fibers in unit length are higher. The numbers of fibers present in the yarn structure are directly proportional to the ultimate product, that is, knitted fabric. The weight of unit area

also increases or decreases, respectively, [19] due to fiber trappings. Similar results are admitted by other researchers that in same manufacturing conditions the breaking strength, tearing strength, abrasion resistance, and crease recovery properties of fabric are improved in case of DRF yarn than plies yarn [20].

3.4. Adequacy of Models. The comparative analysis between actual and predicted performances of DRF yarn knitted fabric is shown by line diagram as given in Figures 2(a) to 2(c). The discussions are as follows.

Figure 2(a) depicts that trend is almost similar in actual and predicted weight per square meter. The actual weight per square meter was maximum at 206, minimum at 184, and average at 192.27; however, predicted weight per square meter was maximum at 203.50, minimum at 184.54, and average at 192.95, respectively.

Figure 2(b) depicts that abrasion cycles trend of predicted values is different from the actual values up to maximum values; therefore, it remains almost the same. The actual abrasion cycles were maximum at 1325, minimum at 1150, and average at 1236.67; however, predicted actual cycles were maximum at 1315.21, minimum at 1169.16, and average at 1263.78, respectively.

Figure 2(c) depicts that bursting strength trend of predicted values is different from the actual values. The actual bursting strength values were maximum at 14.35, minimum at 12.00, and average at 13.09; however, predicted bursting strength values were maximum at 12.90, minimum at 11.33, and average at 12.12, respectively.

The coefficients of correlation (R^2) between observed and predicted values were 0.96, 0.71, and 0.86 for weight, abrasion, and bursting, respectively, which shows significant influence.

The difference (%) was maximum at 1.21, 2.01, and 17.84, minimum at -1.45, -7.26, and -6.61, and average at -0.37, -2.27, and 7.12 for weight, abrasion, and bursting, respectively.

The accuracy (%) was maximum at 101.45, 107.27, and 106.61, minimum at 98.79, 97.99, and 82.16, and average at 100.37, 102.27, and 92.88 for weight, abrasion, and bursting, respectively.

The Discrepancy Factor (R -Factor) was noted to be 0.016, 0.002, and 0.229 for weight, abrasion, and bursting, respectively.

The values under L -estimation are as follows.

The values of ratio were maximum at 1.01, 1.02, and 1.22, minimum at 0.99, 0.93, and 0.94, and average at 1.00, 0.98, and 1.08 for weight, abrasion, and bursting, respectively.

The multiple-ratios were calculated maximum at 1.26, minimum at 0.86, and average at 1.05.

The values of ratio products were calculated maximum at 1.22, minimum at 0.92, and average at 1.06.

The values of toting ratio were calculated maximum at 1.02, minimum at 0.94, and average at 0.98.

4. Conclusions

- (1) The second-order model is the most frequently used approximating polynomial model in RSM. The

FIGURE 2: Comparative analysis: actual versus predicted performances.

Box-Behnken is the most suited design for optimization and prediction of data in textile manufacturing and this model is well-suited for DRF technique yarn knitted fabric.

- (2) The higher wool fiber length shows higher fabric weight, abrasion, and bursting strength.
- (3) The correlation of TM is not visible.

- (4) The role of strands spacing is dominant in comparison to other variables; at 14 mm spacing it shows optimum behaviors.
- (5) The optimum were weight (gms/mt²) 206 at length 75 mm, TM 2.5 and 14 mm spacing, abrasion (cycles) 1325 at length 70 mm, TM 2.25 and 14 mm spacing, bursting (kg/cm²) 14.35 at length 70 mm, and TM 2.00 and 18 mm spacing.

- (6) The variables have substantial influence.
- (7) The adequacies of response surface equations are very high.
- (8) The line trends of knitted fabric basic characteristics were almost the same for actual and predicted models.
- (9) The difference (%) was in range of 1.21 to -1.45, 2.01 to -7.26, and 17.84 to -6.61, the accuracy (%) was in range of 101.45 to 98.79, 107.27 to 97.99, and 106.61 to 82.16, and the Discrepancy Factor (*R*-Factor) was noted to be 0.016, 0.002, and 0.229 for weight, abrasion, and bursting, respectively, between actual and predicted data.
- (10) The *L*-estimation factors for actual and predicted data were that (i) ratio was in range of 1.01 to 0.99, 1.02 to 0.93, and 1.22 to 0.94 for weight, abrasion, and bursting, respectively, (ii) the multiple-ratio was in range of 1.26 to 0.86, (iii) the ratio product was in range of 1.22 to 0.92, and (iv) the totting ratio was in range of 1.02 to 0.94.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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