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ORIGINAL CONTRIBUTION

A Multivariate Quality Loss Function Approach for Optimization of Spinning Processes

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Abstract Recent advancements in textile industry have given rise to several spinning techniques, such as ring spinning, rotor spinning etc., which can be used to produce a wide variety of textile apparels so as to fulfil the end requirements of the customers. To achieve the best out of these processes, they should be utilized at their optimal parametric settings. However, in presence of multiple yarn characteristics which are often conflicting in nature, it becomes a challenging task for the spinning industry personnel to identify the best parametric mix which would simultaneously optimize all the responses. Hence, in this paper, the applicability of a new systematic approach in the form of multivariate quality loss function technique is explored for optimizing multiple quality characteristics of yarns while identifying the ideal settings of two spinning processes. It is observed that this approach performs well against the other multi-objective optimization techniques, such as desirability function, distance function and mean squared error methods. With slight modifications in the upper and lower specification limits of the considered quality characteristics, and constraints of the non-linear optimization problem, it can be successfully applied to other processes in textile industry to determine their optimal parametric settings.

Keywords Quality loss function · Slub yarn · Rotor spinning · Process parameter · Response

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Introduction

In modern textile industry, several spinning techniques are used to commercially produce spun yarns having diverse quality characteristics. Among them, ring spinning is the most commonly and widely adopted technique, which provides the highest quality level of spun yarns with respect to flexibility and strength. However, one of its major drawbacks is its low production rate as compared to other new spinning techniques, like rotor spinning, air jet spinning, friction spinning etc. A typical rotor spinning setup takes up comparatively less floor space and machinery, and fewer spare parts, which ultimately result in less energy and maintenance cost, and much less labour force, resulting in higher worker efficiency [1]. With respect to quality, rotor spinning suffers a limitation in yarn strength as compared to ring spinning due to their inherent structural differences. Yarn breakage rate is also relatively lower in rotor spinning in comparison to ring spinning, which results in higher production rate.

Cotton yarns produced by spinning have a wide range of applications in textile industry, not only in clothing, but also for several other purposes. Numerous quality characteristics of spun yarn, like yarn strength (breaking tenacity), unevenness, hairiness, degree of imperfections, effect retention (abrasion resistance on usage) etc. decide its ultimate applicability in different domains. An acceptable yarn quality characteristic mainly depends on its particular end use. Lower yarn strength may be suitable for knitting, but it would not be appropriate for weaving.

In case of rotor spinning process, several controllable parameters (or factors), like rotor speed, yarn twist level etc. significantly affect different quality characteristics of the final yarn. Yarns are also occasionally produced with slubs for providing some aesthetic qualities to the fabrics.

In slub spinning process, input parameters, such as slub thickness, slub length, slub frequency etc. have different degrees of influence on the ultimate quality of fabric. However, satisfying several quality characteristics simultaneously at a single parametric setting of a spinning process is a challenging task for the quality engineers. A priori knowledge on the optimal parametric combination in a spinning process would help them in achieving the desired quality characteristics. Several mathematical tools are already available for the quality engineers which guides them in identifying the optimal parametric settings which would satisfy several yarn quality characteristics. In this paper, a multivariate quality loss function approach is employed to simultaneously optimize multiple yarn characteristics, while aiming to minimize the total loss in quality of the considered product. A comparative analysis with respect to the other state-of-the-art multi-objective optimization tools is also carried out so as to establish the potentiality and applicability of this approach in optimizing multiple yarn quality characteristics simultaneously.

Literature Review

Applying mechanistic, statistical and neural network models, Guha et al. [2] predicted the yarn tenacity of polyester staple fabric, and also established the superiority of neural network models over the other two adopted approaches. Sette and Van Langenhove [3] carried out constrained optimization on blend coefficients of a fibre-to-yarn production process, while including several real time constraints. Van Langenhove and Sette [4] applied a soft computing approach with the help of neural networks to optimize price, yarn characteristics, spinnability and production constraints of fibre-to-yarn transformation processes. Majumdar et al. [5] applied artificial neural network models for predicting single yarn tenacity of ring and rotor-spun yarns based on different cotton fibre properties, confirming their superiority while comparing the predicted yarn tenacity values with the actual ones. Majumdar et al. [6] studied the performance of different models (regression and artificial neural network), optimization tools (linear programming, genetic algorithm etc.) and decision making techniques (analytic hierarchy process and technique for order preference by similarity to ideal solution (TOPSIS)) for the design of functional clothing. Arain et al. [7] employed desirability function approach to optimize multiple quality characteristics of rotor spun yarn, i.e. yarn strength, unevenness, hairiness and imperfections, while determining the best combination of rotor speed and yarn twist level. Jeyaraj et al. [8] identified the optimal processing conditions in a color fast finishing process while applying genetic algorithm as a multi-objective optimization tool. Ghosh et al. [9] presented the application of non-dominated sorting genetic algorithm II (NSGA-II) to simultaneously optimize cotton yarn strength and raw material quality while identifying the optimal combination of various fibre properties. Das and Ghosh [10] explored the applicability of simulated annealing (SA) technique to find out the optimal combination of various fibre properties, i.e. fibre linear density, elongation at break, average fibre length and fibre tenacity for production of ring spun cotton yarn. The SA technique was mainly applied for solving the constrained optimization problem derived from Frydrych's yarn strength equation. Hasanuzzaman et al. [11] adopted desirability function approach to find out the optimal combination of different ring spinning process parameters, such as spindle speed, roving twist multiplier and yarn twist multiplier, for various yarn quality characteristics which include yarn breakage rate, specific strength, irregularity, breaking extension, hairiness index and imperfections. Majumdar et al. [12] employed a hybrid approach while integrating artificial neural networks for modelling and genetic algorithm for optimization of the woven fabric parameters for having the optimal ultraviolet protection and comfort properties. Mukhopadhyay et al. [13] employed TOPSIS method on a set of optimal parametric combinations derived from the application of a multi-objective evolutionary algorithm for injected slub yarn in order to achieve the least abrasion damage on fabrics produced from it. Different structural parameters of the injected slub yarn, like slub length, slub thickness and slub frequency were separately considered for various quality characteristics of both woven and knitted fabrics. The quality characteristics were broadly classified into yarn strength properties, yarn abrasion damage properties and abrasion damage on fabrics. Majumdar et al. [14] employed NSGA-II technique to simultaneously optimize two conflicting quality characteristics of knitted fabric, i.e. air permeability and thermal conductivity, with a desired ultraviolet protection factor.

From the abovecited literature, it can be inferred that since the last few years, parametric optimization of various textile manufacturing processes has been a topic of immense interest among the researchers. Taguchi loss function approach has been proven to be an effective tool in single objective optimization of the responses. However, it fails to deliver accurate and reliable solutions when multiple quality characteristics are involved. As quite evident from the literature, multi-objective optimization is the present day need of the textile industry in order to determine the best parametric mixes of its several production processes. Hence, in this paper, a mathematical tool in the form of multivariate quality loss function approach is applied which aims at providing the optimal combinations of different spinning parameters while fulfilling the target values of multiple quality characteristics (responses).

Multivariate Loss Function

The concept of quality loss dates back to G. Taguchi, when he cleverly phrased quality of a product in terms of the loss incurred to the society or industry, due to its harmful side effects, and its incapability to adhere to the needs of the society or industry. Quality can be quantified with the help of several characteristics, all of which depend on a common set of parameters. Taguchi proposed a quality loss function, which would approximately quantify the deviation of a characteristic from its set target, from a customer's point of view [15].

$$Loss(y) = k(y - t)^2 \tag{1}$$

where y is the quality characteristic of a product, t is the target value of the characteristic and k is a quality loss coefficient. In order to define this quality loss coefficient such that the resultant quality loss is insensitive to the units used to quantify the quality characteristics, Artiles-León [16] assumed a relationship between each quality characteristic and the design variables. Since, majority of the quality characteristics are of 'nominal-the-best' type, it could be assumed that the target would be positioned at the centre of the specification limits, where quality loss would be zero, whereas, at the upper and lower specification limits, the quality loss function would give a value of one. Thus, for 'nominal-the-best' type of quality characteristic, the value of k can be defined as $k = \left(\frac{2}{USL-LSL}\right)^2$ and the corresponding quality loss function can be formulated using Eq. (2).

$$Loss(y) = 4\left(\frac{y(x) - t}{USL - LSL}\right)^2 \tag{2}$$

Artiles-León [16] defined a total standardized quality loss function corresponding to n such 'nominal-the- best' type quality characteristics, $Y_1, Y_2, \ldots, Y_n$, as follows:

$$TSLoss(Y_1, Y_2, \ldots, Y_n, X, T) = 4\sum_{i=1}^{n}\left(\frac{Y_i(x) - t_i}{USL_i - LSL_i}\right)^2 \tag{3}$$

where $Y_1, Y_2, \ldots, Y_n$ are the quality characteristics, T is $t_1, t_2, t_3, \ldots, t_n$ target values of n characteristics, and USL_i and LSL_i are the upper and lower specification limits for i^{th} quality characteristic respectively. However, such an assumption is only fit for 'nominal-the-best' type of characteristics, and does not provide any guidance for 'smaller-the-better' and 'larger-the-better' types of quality characteristics. Ma and Zhao [17] developed an improved multivariate loss function which could include all types of quality characteristics. For 'larger-the-better' type of quality characteristic, the target value is assumed to be the upper specification limit, and the quality loss at lower specification limit is one. For this case, the corresponding value of the quality loss coefficient, k is defined as $k = \left(\frac{1}{USL-LSL}\right)^2$ and a quality loss function is formulated using Eq. (4).

$$Loss(Y_i(X), X, USL_i) = \left(\frac{y_i(x) - USL_i}{USL_i - LSL_i}\right)^2 \tag{4}$$

Similarly, for 'smaller-the-better' type of quality characteristic, the target value is assumed to be at the lower specification limit, and the corresponding quality loss at upper specification limit is one. The related quality loss function is defined in Eq. (5).

$$Loss(Y_i(X), X, LSL_i) = \left(\frac{y_i(x) - LSL_i}{USL_i - LSL_i}\right)^2 \tag{5}$$

As all of these expressions are dimensionless, they can be combined together to form a generalized multivariate quality loss function through Eq. (6).

$$\begin{aligned} Loss(Y(X), X) = 4\sum_{i=1}^{N}\left(\frac{Y_i(x) - t_i}{USL_i - LSL_i}\right)^2 &+ \sum_{j=1}^{L}\left(\frac{Y_j(x) - USL_j}{USL_j - LSL_j}\right)^2 \\ &+ \sum_{k=1}^{S}\left(\frac{Y_k(x) - LSL_k}{USL_k - LSL_k}\right)^2 \end{aligned} \tag{6}$$

where N is the number of quality characteristics of 'nominal-the-best' type, L is the number of characteristics of 'larger-the-better' type and S is the number of characteristics of 'smaller-the-better' type.

Illustrative Examples

In this section, the multivariate loss function approach is applied for multi-response optimization of several quality characteristics of slub and rotor-spun yarns, and the derived results are subsequently compared with the other state-of-the-art optimization methodologies.

Example 1

Mukhopadhyay et al. [13] considered slub length, slub thickness and slub frequency as the three important parameters of injected slub yarn, and conducted experiments in order to achieve the least abrasive damage on fabrics produced from it. Using ring spinning technique, and based on the Box and Behnken experimental design plan with five central points, a total of 17 samples were

Table 1 Different parameters and their levels for example 1 [13]

Parameter	Symbol	Level		
		− 1	0	1
Slub length (mm)	x_1	30	65	100
Slub thickness (%)	x_2	140	170	200
Slub frequency (slubs/m)	x_3	1.5	2.5	3.5

produced, and subsequently used for knitted and woven fabric samples. Each of those input parameters was divided into three different levels, as shown in Table 1.

During the experimental analysis, nine quality characteristics were considered, i.e. Y_1 (yarn tenacity), Y_2 (yarn elongation %), Y_3 (yarn hairiness rise), Y_4 (yarn tenacity loss), Y_5 (yarn elongation loss), Y_{sk} (surface damage of knitted fabric), Y_{mk} (mass loss of knitted fabric), Y_{sw} (surface damage of woven fabric) and Y_{mw} (mass loss of woven fabric). Among those quality characteristics, yarn tenacity and yarn elongation are the beneficial ('larger-the-better' type) attributes, whereas, the remaining are the non-beneficial ('smaller-the-better' type) attributes. Based on the experimental observations, the following regression equations were subsequently developed showing the interrelationships between the slub yarn parameters and the considered quality characteristics.

$$Y_1 = 15.584 - 0.608x_1 - 0.91x_2x_3 \tag{7}$$

$$Y_2 = 5.108 + 0.465x_3 - 0.42x_1x_2 \tag{8}$$

$$Y_3 = 2.389 + 0.330x_1x_2 + 0.492x_1x_3 \tag{9}$$

$$Y_4 = 2.590 - 0.481x_1 - 0.391x_3 - 0.467x_3^2 - 0.480x_1x_3 \tag{10}$$

$$Y_5 = 1.570 + 0.253x_3 + 0.294x_1^2 - 0.288x_1x_3 \tag{11}$$

$$\begin{aligned} Y_{sk} = 8.856 + 1.12x_2 - 1.071x_3 - 3.498x_2^2 \\ + 3.679x_3^2 + 3.643x_2x_3 \end{aligned} \tag{12}$$

$$\begin{aligned} Y_{mk} = 7.676 - 0.370x_2 - 0.435x_3 + 1.072x_1^2 \\ + 1.642x_2^2 - 0.387x_3^2 + 0.840x_1x_2 - 0.815x_2x_3 \end{aligned} \tag{13}$$

$$Y_{sw} = 9.00 - 2.374x_1 - 2.357x_2 - 2.661x_3 - 2.035x_2x_1 \tag{14}$$

$$Y_{mw} = 2.909 + 0.350x_1 - 0.425x_3 + 0.797x_1^2 + 0.667x_3^2 \tag{15}$$

The specification limits for all the quality characteristics were fixed according to the industrially acceptable standards (threshold values), as provided in Table 2. The target value is set to be either maximum or minimum depending on the type of the quality characteristic.

Based on these set specification limits, the corresponding multivariate loss function is defined, separately for knitted fabrics and woven fabrics.

Table 2 Criteria level for optimization of parameters [13]

Quality characteristic	Acceptable standard
Yarn tenacity (Y_1)	> 14.0
Yarn elongation % (Y_2)	> 4.50
Yarn hairiness rise (Y_3)	< 2.50
Tenacity loss on abrasion (Y_4)	< 2.80
Elongation loss on abrasion (Y_5)	< 1.50
Surface damage for knitted fabric (Y_{sk})	< 9.57
Mass loss for knitted fabric (Y_{mk})	< 8.38
Surface damage for woven fabric (Y_{sw})	< 9.29
Mass loss for woven fabric (Y_{sw})	< 3.41

Case 1: Knitted Fabric

Minimize

$$\begin{aligned} & Loss(Y_1, Y_2, Y_3, Y_4, Y_5, Y_{sk}, Y_{mk}) \\ & = \left(\frac{Y_1 - 16.9}{2.9}\right)^2 + \left(\frac{Y_2 - 5.9}{1.4}\right)^2 + \left(\frac{Y_3 - 1.57}{0.93}\right)^2 + \left(\frac{Y_4 - 0.8}{2}\right)^2 \\ & + \left(\frac{Y_5 - 1.25}{0.25}\right)^2 + \left(\frac{Y_{sk} - 2.87}{6.7}\right)^2 + \left(\frac{Y_{mk} - 6.7}{1.68}\right)^2 \end{aligned} \tag{16}$$

Subject to

$$14.0 \le Y_1 \le 16.9 \tag{17}$$

$$4.5 \le Y_2 \le 5.9 \tag{18}$$

$$1.57 \le Y_3 \le 2.50 \tag{19}$$

$$0.8 \le Y_4 \le 2.8 \tag{20}$$

$$1.25 \le Y_5 \le 1.50 \tag{21}$$

$$2.87 \le Y_{sk} \le 9.57 \tag{22}$$

$$6.70 \le Y_{mk} \le 8.38 \tag{23}$$

$$x_1^2 + x_2^2 + x_3^2 \le 1 \tag{24}$$

The regression equations, as shown in Eqs. (7–15), are individually optimized using genetic algorithm with respect to various constraints imposed by the ranges of values for different input parameters, and the corresponding maximum and minimum values for 'larger-the-better' and 'smaller-the-better' types of quality characteristics are respectively determined. The derived maximum value is set as the upper specification limit for 'larger-the-better' and the minimum value is considered as the lower specification limit for 'smaller-the-better' types of quality characteristics. Mukhopadhyay et al. [13] solved those regression equations using a multi-objective optimization algorithm of MATLAB software in order to identify the optimal combination of slub yarn parameters for attaining the desired level of knitted fabric

Table 3 Multi-objective optimization results for knitted fabric

	Method	
	Mukhopadhyay et al. [13]	Quality loss function
Parameter		
Slub length (x_1)	60.03	48.9520
Slub thickness (x_2)	159.20	187.0153
Slub frequency (x_3)	2.1	2.0821

	Mukhopadhyay et al. [13]	Quality loss function	Improvement (%)
Quality characteristic			
Tenacity (Y_1)	15.5	16.0785	3.73
Breaking elongation (Y_2)	4.9	5.0229	2.51
Hairiness index rise (Y_3)	2.4	2.3974	0.11
Tenacity loss (Y_4)	2.71	2.6900	0.74
Breaking elongation loss (Y_5)	1.45	1.3473	7.08
Surface damage (Y_{sk})	9.54	8.5925	9.93
Mass loss (Y_{mk})	8.08	8.0386	0.51

abrasion resistance. For knitted fabric, 15 different optimal combinations were obtained. Those optimal solutions in the form of parametric combinations were further processed using TOPSIS method so as to determine the best suited parametric mix. It was concluded that the parametric combination of slub length = 60.03 mm, slub thickness = 159.20% and slub frequency = 2.1 slubs/m would provide the optimal solution for achieving the least abrasive damage of knitted fabric. Now, while solving the developed non-linear multivariate loss function with respect to the given linear and non-linear constraints using the optimization toolbox of MATLAB software, it is revealed that a parametric combination of slub length = 48.9520 mm, slub thickness = 187.0153% and slub frequency = 2.0821 slubs/m offers the optimal solution for having the least abrasive damage of knitted fabric. Linear constraints are those constraints which vary linearly with different spinning process parameters, whereas, non-linear constraints vary non-linearly. In this example, the developed regression equations for different quality characteristics are treated as the constraints. As these equations involve non-linear interaction terms between different spinning parameters, they are termed as non-linear constraints. Another non-linear constraint of Eq. (24) is derived from the fact that the optimal settings should be constrained to reside on or within the sphere defined by the experimental design plan. Table 3 shows a comparison between the results derived by Mukhopadhyay et al. [13] and the adopted quality loss function approach. From this table, it is interestingly noticed that for all the considered quality characteristics of the knitted fabric, there are marked improvements in their achieved values. Among these quality characteristics, breaking elongation loss and abrasive surface damage of knitted fabric are significantly reduced by 7.08 and 9.93% respectively. The solutions of the same problem as derived using the multivariate loss function approach are also compared with those obtained while employing desirability function [18], mean squared error [19] and distance function [20] methods, as exhibited in Table 4. This comparison of the derived results also confirms the superiority of multivariate loss function approach over the other state-of-the-art multi-objective optimization methods in identifying the optimal combination of slub yarn parameters.

Desirability function approach assigns a desirability value to each quality characteristic such that the desirability of a quality characteristic Y_i is 0, when Y_i gives the worst value; 1 when Y_i provides the best value; and for any intermediate value of Y_i, the desirability value is interpolated between 0 and 1. This approach has become quite popular for multi-response optimization problems, where the composite desirability, considering all the quality characteristics together, is the geometrical mean of the desirabilities for the individual characteristics, as given in the following expression:

$$\text{Maximize}\,(D) = (d_1(Y_1)d_2(Y_2)d_3(Y_3)\ldots d_n(Y_n))^{1/n} \quad (25)$$

where $d_i(Y_i)$ is the desirability of ith quality characteristic.

In mean square error method, the total loss incurred from multiple quality characteristics is computed and the total loss function is defined as follows:

$$\text{Minimize}\,[E(L)] = \sum_{i=1}^{n} (Y_i(x) - t_i)^2 \quad (26)$$

where t_i are the target value of ith characteristic.

Table 4 Comparison of results derived using different multi-objective optimization methods for knitted fabric

	Method			
	Quality loss function	Desirability function	Mean squared error	Distance function
Parameter				
Slub length (x_1)	48.9520	53.5359	50.9722	50.3058
Slub thickness (x_2)	187.0153	157.0342	158.2894	158.6287
Slub frequency (x_3)	2.0821	2.1011	2.4382	2.4514
Quality characteristic				
Tenacity (Y_1)	16.0785	15.6263	15.8057	15.8225
Breaking elongation (Y_2)	5.0229	4.8631	5.0135	5.0186
Hairiness index rise (Y_3)	2.3974	2.5000	2.4528	2.4516
Tenacity loss (Y_4)	2.6900	2.7661	2.7932	2.8000
Breaking elongation loss (Y_5)	1.3473	1.3999	1.5000	1.5000
Surface damage (Y_{sk})	8.5925	9.3593	8.6539	8.6568
Mass loss (Y_{mk})	8.0386	8.3480	8.3800	8.3800

In distance function approach, the following simplistic formulation is adopted:

$$\text{Minimize } [L] = \left[\sum_{i=1}^{n} \frac{(Y_i(x) - t_i)^2}{t_i^2}\right]^{1/2} \quad (27)$$

Case 2: Woven Fabric

For woven fabric, the following multivariate loss function model is formulated:Minimize

$$Loss(Y_1, Y_2, Y_3, Y_4, Y_5, Y_{sw}, Y_{mw}) = \left(\frac{Y_1 - 16.9}{2.9}\right)^2 + \left(\frac{Y_2 - 5.9}{1.4}\right)^2 + \left(\frac{Y_3 - 1.57}{0.93}\right)^2 + \left(\frac{Y_4 - 0.8}{2}\right)^2 + \left(\frac{Y_5 - 1.25}{0.25}\right)^2 + \left(\frac{Y_{sw} - 0}{9.29}\right)^2 + \left(\frac{Y_{mw} - 2.8}{0.61}\right)^2 \quad (28)$$

Subject to

$$14.0 \le Y_1 \le 16.9 \quad (29)$$

$$4.5 \le Y_2 \le 5.9 \quad (30)$$

$$1.57 \le Y_3 \le 2.50 \quad (31)$$

$$0.8 \le Y_4 \le 2.8 \quad (32)$$

$$1.25 \le Y_5 \le 1.50 \quad (33)$$

$$0 \le Y_{sw} \le 9.29 \quad (34)$$

$$2.80 \le Y_{mw} \le 3.41 \quad (35)$$

$$x_1^2 + x_2^2 + x_3^2 \le 1 \quad (36)$$

The solutions derived from the developed non-linear multivariate loss function are again compared with those obtained by Mukhopadhyay et al. [13], and other multi-objective optimization methods, as shown in Tables 5 and 6 respectively. From Table 5, it can be observed that there are improvements in all the considered quality characteristics, with the most significant improvements in breaking elongation and hairiness index rise in woven fabric by 2.90 and 3.64% respectively. It can also be revealed that the adopted multivariate loss function approach performs well against desirability function, distance function and mean squared error methods in optimizing multiple responses. Thus, an optimal parametric combination of slub length = 51.1316 mm, slub thickness = 200% and slub frequency = 2.2212 slubs/m is prescribed to achieve the least abrasive damage of woven fabric.

Example 2

In this example, the experimental data of Arain et al. [7] are taken into consideration for subsequent solution using the multivariate loss function approach in order to determine the optimal parametric mix of a rotor spinning process. Arain et al. [7] conducted experiments on cotton yarn of 30 tex in a rotor spinning machine while varying two input parameters, i.e. rotor speed and yarn twist level at four different levels. Table 7 depicts the actual and coded values of those two rotor spinning process parameters. Four yarn quality characteristics, such as yarn strength (Y_1) (in cN/tex), unevenness (Y_2) (in CVm %), hairiness (Y_3) and yarn imperfections (Y_4) were considered as the important responses. Among those responses, yarn tenacity is the only 'higher-the-better' type of quality characteristic, whereas, yarn hairiness, unevenness and imperfections are the 'lower-the-better' type of quality characteristics. Based on the experimental observations and using response surface methodology, the following polynomial equations

Table 5 Multi-objective optimization results for woven fabric

	Method		
	Mukhopadhyay et al. [13]		Quality loss function
Parameter			
Slub length (x_1)	60.03		51.1316
Slub thickness (x_2)	188		200.0000
Slub frequency (x_3)	2.1		2.2212
	Mukhopadhyay et al. [13]	Quality loss function	Improvement (%)
Quality characteristic			
Tenacity (Y_1)	15.9	16.0786	1.12
Breaking elongation (Y_2)	5.0	5.1448	2.90
Hairiness index rise (Y_3)	2.4	2.3126	3.64
Tenacity loss (Y_4)	2.71	2.7050	1.84
Breaking elongation loss (Y_5)	1.45	1.4215	1.97
Surface damage (Y_{sw})	9.16	9.1318	0.31
Mass loss (Y_{mw})	3.15	3.0658	2.67

Table 6 Comparison of results derived using different multi-objective optimization methods for woven fabric

	Method			
	Quality loss function	Desirability function	Mean squared error	Distance function
Parameter				
Slub length (x_1)	51.1316	58.7676	86.7047	79.7466
Slub thickness (x_2)	200.0000	200.0000	142.8664	200.0000
Slub frequency (x_3)	2.2212	2.1974	3.0788	2.3647
Quality characteristic				
Tenacity (Y_1)	16.0786	15.9676	15.6833	15.4509
Breaking elongation (Y_2)	5.1448	5.0421	4.6127	4.8681
Hairiness index rise (Y_3)	2.3126	2.3567	2.3805	2.5000
Tenacity loss (Y_4)	2.7050	2.8000	2.7980	2.7583
Breaking elongation loss (Y_5)	1.4215	1.4686	1.5000	1.5000
Surface damage (Y_{sw})	9.1318	9.2333	9.2609	9.1453
Mass loss (Y_{mw})	3.0658	3.1616	3.4100	3.2676

Table 7 Different rotor spinning parameters and their corresponding levels

Parameter	Level			
	1	2	3	4
Rotor speed (x_1) (rpm)	70000	80000	90000	100000
Yarn twist (x_2) (TPM)	500	550	600	700

were also developed presenting the relationships between the rotor spinning process parameters and yarn quality characteristics.

$$Y_1 = -23.568 + 0.00035x_1 + 0.05271x_2 - 1.92333E^{-9}x_1^2 - 3.27182E^{-5}x_2^2 \quad (37)$$

$$Y_2 = 25.8516 - 3.28901E^{-4}x_1 + 2.10938E^{-9}x_1^2 \quad (38)$$

$$Y_3 = 15.5734 - 2.17571E^{-4}x_1 - 0.00234x_2 + 1.26251E^{-9}x_1^2 \quad (39)$$

$$Y_4 = 2516.21 - 0.06916x_1 + 0.40028x_2 + 4.43751E^{-7}x_1^2 \quad (40)$$

Now, based on the experimental observations of Arain et al. [7], the following multivariate total quality loss

Table 8 Multi-objective optimization results for example 2

	Method			
	Arain et al. [7]	Quality loss function	Mean squared error	Distance function
Parameter				
Rotor speed (x_1)	85000	80202	80575	80543
Yarn twist (x_2)	600	617	615	615
Quality characteristic				
Yarn tenacity (Y_1)	11.9	12.2025	12.189	12.1901
Yarn unevenness (Y_2)	13.1	13.0414	13.0452	13.0448
Yarn hairiness (Y_3)	4.8	4.7329	4.9549	4.9548
Yarn imperfections (Y_4)	84	75.7466	77.6354	77.6542

function is developed for subsequent solution using MATLAB software.Minimize

$$Loss(Y_1, Y_2, Y_3, Y_4) = \left(\frac{Y_1 - 13.2}{2}\right)^2 + \left(\frac{Y_2 - 13}{2}\right)^2 + \left(\frac{Y_3 - 4.5}{0.5}\right)^2 + \left(\frac{Y_4 - 50}{100}\right)^2 \tag{41}$$

Subject to

$$11.2 \leq Y_1 \leq 13.2 \tag{42}$$

$$13 \leq Y_2 \leq 15 \tag{43}$$

$$4.5 \leq Y_3 \leq 5 \tag{44}$$

$$50 \leq Y_4 \leq 100 \tag{45}$$

Arain et al. [7] adopted desirability function approach for optimization of the considered multiple responses according to the top 5% quality level characteristic specifications, and obtained the response values as yarn tenacity = 11.9 cN/tex, yarn unevenness = 13.1, yarn hairiness = 4.8 and yarn imperfections = 84 for a parametric setting of rotor speed = 85000 rpm and yarn twist level = 600. When the developed quality loss function model is solved, the values of various quality characteristics are obtained as yarn tenacity = 12.2025 cN/tex, yarn unevenness = 13.0414, yarn hairiness = 4.7329 and yarn imperfections = 75.7466 at an optimal parametric mix of rotor speed = 80202 rpm and yarn twist level = 615. It can be observed from the results of Table 8 that all the four quality characteristics are improved in the multivariate loss function approach, with the most significant reduction in yarn imperfections by 9.83% (from 84 to 75.7466). These derived solutions are also compared with mean squared error and distance function methods, and it can be observed that the multivariate loss function approach excels over the other multi-objective optimization techniques while achieving the best possible combination of the rotor spinning process parameters for having the most desired yarn quality characteristics. The improved performance of multivariate loss function approach can be owed to the fact that in this method, the losses corresponding to different quality characteristics are expressed in a uniform unit with loss values spanning from 0 to 1, and the combined loss is expressed as a scalar sum of the individual losses.

Conclusions

In textile industry, various types of new spinning techniques have emerged with different benefits and limitations over the traditional techniques, such as ring spinning process. Thus, it calls for deployment of different mathematical tools and techniques to identify the optimal parametric settings for those new spinning processes while simultaneously optimizing several quality characteristics of cotton yarns. In this paper, an almost unexplored tool in the form of multivariate quality loss function approach is applied for multi-objective optimization of two different yarn manufacturing processes, and the derived results establish the potentiality and flexibility of this approach in determining the optimal parametric combinations of those processes. This approach expresses the loss of different quality characteristics in a uniform unit with a range of values from 0 to 1, where 0 represents poor quality and 1 signifies best quality. With this approach, several quality characteristics can be integrated together to form a total quality loss function, which is adept in finding out the optimal solution. Like TOPSIS method, in this approach too, weight (relative importance) can be assigned to each of the quality characteristics so as to derive more realistic optimal solutions with respect to the settings of various spinning process parameters. The TOPSIS method can be visualized as a discrete optimization tool where the derived optimal settings of different spinning parameters can only take among those values as selected during the experimental runs. On the other hand, the multivariate quality loss function approach can take any value for a particular spinning process parameter within the considered range leading to almost global solution for a multi-objective optimization problem. Citing the improvements in the obtained results, it can be concluded that this approach is suitable for extensive use in multi-objective optimization of various quality characteristics in textile industry as well as in other process industries.

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