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Genetic Algorithm Based Multi-Objective Optimization of Process Parameters in Color Fast Finish Process - A Textile Case Study

K.L. Jeyaraj and C. Muralidharan
Annamalai University

T. Senthilvelan
Pondicherry Engineering College

S.G. Deshmukh
Indian Institute of Technology Delhi
India

ABSTRACT

This study describes the application of intelligent control systems in color fast finish (CFF) process as well as to use these approaches for optimizing processing conditions. A multi-objective optimization method based on genetic algorithm (GA) has been proposed for the design and control of color fast finish process. The processing parameters including temperature of the pre-dryer, bath liquor pickup, machine speed and padder pressure were used as design variables and were mathematically related to the five quality characteristics; shade variation to the standard, color fastness to washing, center to selvedge variation, color fastness to light and fabric residual shrinkage using response surface methodology (RSM) technique. Nonlinear mathematical functions were derived based on the processing parameters. Afterward, using a multi-objective optimization technique based on genetic algorithm, optimal conditions were found in such a way that, mean color fast finish process parameters were optimized.

Keywords: Response surface methodology, GA, Multi-objective optimization, Color fast finish, Textile industry

1.0 Introduction

Finishing in the narrow sense is the final step in the fabric manufacturing process. Finishing completes the fabric's performance and gives it special functional properties including the final touch. The term finishing is also used in its broad sense: "Any operation for improving the appearance or usefulness of a fabric after it leaves the loom or the knitting machine can be considered as a finishing step" (Schindler & Hauser, 2004). The management of the finishing factory is very difficult, particularly because it is necessary to avoid long lead time, idle time, fabric quality and environmental issues. The goal is to implement better and efficient processing method than the time consuming conventional methods. In fact, the cost of finishing treatment is so elevated, that it represents 25.7% of the costs of materials textile preparation to get finished product. The expenses in energy and the water consumption represent 15 to 21% of the finishing cost (Rouette, 2000). So, two problems must be solved simultaneously in the textile finishing plants: minimization of time and energy cost (Kordoghli, Jmali, Saadallah, & Liouene, 2010). For tackling these problems, organization has to focus on identifying improved manufacturing methods with the safe environmental perspectives.

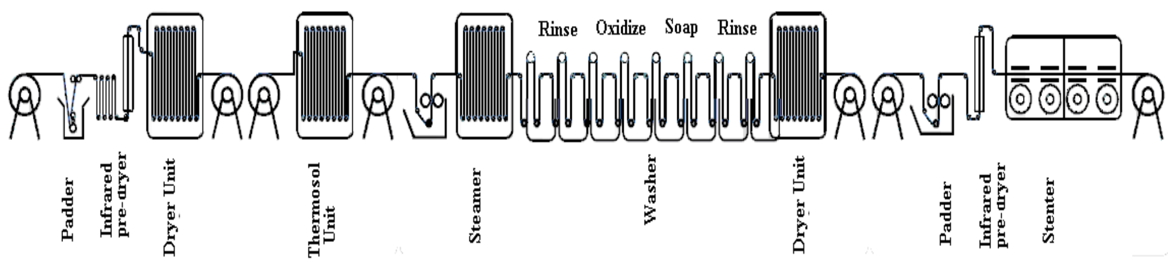


Figure 1. Conventional method of textile dyeing and finishing flow diagram

Color fast finish (CFF) is a shortest textile dyeing and finishing process, which enables to do impregnation, drying and curing in a straight forward single operation. In the traditional method of dyeing cotton, polyester (PES) and PES/cotton blend have to be dyed separately before going to finishing (Figure 1). Now, with CFF, this can all be done in single step (Figure 2). The innovative CFF process is much faster than the conventional procedure (BASF, 2012; COLOR-PROFI, 2004). It will save time and energy - which allows you to reduce the overall process costs: less energy, less equipment needed and reduced staff costs. The fact that the total conventional process can be considerably shortened by the CFF provides not only economic benefits, but also considerable ecological benefits: (i) reduced energy consumption, (ii) reduced water use and subsequent wastewater load and (iii) Reduction of CO_2 emissions. However, color fast finish requires lot of attention in parameter study which yields robust and optimized process conditions.

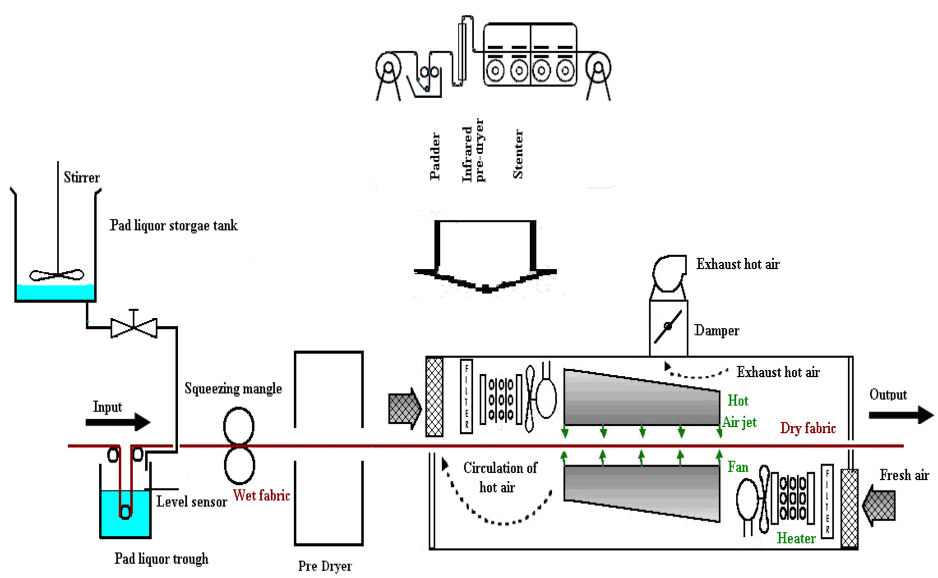


Figure 2. Color fast finish process flow diagram and schematic diagram

In this paper, a multi-objective optimization method, based on a posteriori technique and using genetic algorithm (GA), is proposed to obtain the optimal parameters in color fast finish processes for a robust process development. During the process development both the inputs and outputs of the process are studied. The purpose of these studies is to determine the significant process parameters for the multiple objectives environment. The goal of this development phase is to have a good understanding of the process and relationship of the parameters to attributes. The main objectives of this paper are to:

- Develop the empirical relationship between the response and factors
- Validate the relationship and significance of process parameters
- Optimize the process parameters of CFF process using multiple objective genetic algorithm

This paper is organized as follows: The literature review is presented followed by experimental setup, then methodology used for the study is discussed with a case of a textile company. A main experiment is proposed to select the optimal process parameters with the help of central composite design with analysis. The non-linear relationship between the factors and response is provided. The models are validated with the Anova, normal probability plots and *t*-test. With the help of surface plot and contour plot the individual response models are studied. Then genetic algorithm based multi-objective optimization is performed to find the pareto optimal solutions for considering all the five objectives simultaneously.

2.0 Literature Review

Design problems are generally a natural process to optimize the solution corresponding to specified requirements. The problem can be complex because there are many numbers of design variables and these design variables frequently interact with each other (Montgomery, 2005). To obtain the desired output values, it is essential to have a complete control over the relevant process parameters. Various prediction methods can be applied to define the desired output variables through developing mathematical models to specify the relationship between the input parameters and output variables. The response surface methodology (RSM) is helpful in developing a suitable approximation for the true functional relationship between the independent variables and the response variable that may characterize the nature of the process (Ravikumar, Krishnan, Ramalingam, & Balu, 2006). In any optimization procedure, it is a crucial aspect to identify the output of chief importance, the so-called optimization objective or optimization criterion. In manufacturing processes, the most commonly used optimization criterion is specific cost. Sometimes, other criteria like color strength (Kuo, Chang, Su, & Fu, 2008), fiber properties - fiber diameter and its distribution (Nurwaha & Wang, 2012), dyeing machine scheduling time (Keith, Patrick, Hui, Yeung, & Frency, 1998) and mechanical properties of the textile fabric (Karthikeyan & Sztandera, 2010) have been used too. However, these single objective approaches have a limited value to the optimal processing conditions in textile processing, due to the complex nature of the textile finishing processes, where several different and contradictory objectives must be simultaneously optimized. Some multi-objective approaches have been reported in parameters optimization (Guo, Wong, Leung, Fan, & Chan, 2006; Kordoghli, Jmali, Saadallah, & Liouene, 2010; Lv, Xiang, & Yang, 2011) but mainly they use a priori techniques, where the decision maker combines the different objectives into a scalar cost function. This actually makes the multi-objective problem to a single-objective prior to optimization (Veldhuizen, & Lamont, 2000). On the other hand, in the a posteriori techniques, the decision maker is presented with a set of non-dominated optimal candidate solutions and chooses from that set. These solutions are optimal in the wide sense that no other solution in the search space is superior to them when all optimization objectives are simultaneously considered (Abbass, Sarker, & Newton, 2001). They are also known as Pareto-optimal solutions. Comparing citations by technique in the previous years; evidences the popularity of a posteriori techniques (Veldhuizen, & Lamont, 2000). In dealing with multi-objective optimization problems, classical optimization methods (weighted sum methods, goal programming, min-max methods, etc.) are not efficient, because they cannot find multiple solutions in a single run, thereby requiring them to be applied as many times as the number of desired Pareto-optimal solutions. On the contrary, studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above-mentioned difficulties of classical methods (Soodamani & Liu, 2000).

Genetic algorithms can be used to solve wide variety of problems in textiles right from production of textile fibers to apparel design and manufacturing. Amin, El-Geheni, El-Hawary & El-Beali (2007) have reported detection of the spinning fault source from spectrograms by using genetic algorithm technique. GA was applied to extract fault source from the expert database. The expert database consists of spectrogram specification such as fault category, fault type, spectrogram shape, etc. Lin (2003) investigated the use of GA for searching weaving parameters for woven fabrics. A searching mechanism was developed to find the best combinations of warp and weft counts and yarn densities for fabric manufacturing, considering costs. This helps the designer to select appropriate combinations of these parameters to achieve the required weight of fabric at a pre-controlled cost. Grundler & Rolich (2000) have developed an evolutionary algorithm (GA) for creating different weave patterns. Only the weave and yarn color were considered as attributes for fabric appearance and different patterns can be created by various combination of weave and color of warp and weft threads. Kandi & Tehran (2007) have proposed a color recipe prediction with the use of GA. It has been claimed that the developed method can do both spectro photometric and colorimetric color matching based on its fitness function. It has also been shown that the developed method is capable of decreasing the color difference under second illuminant and reduces metamerism problem by applying a fitness function based on the color differences under two illuminants. Patrick, Frency, & Keith (2000) have studied the application of GA on the roll planning of fabric spreading in apparel manufacturing. It was demonstrated that the use of GAs to optimize roll planning will result in reduced wastage in cutting and hence can reduce cost of apparel production. Keith, Patrick, Hui, Yeung & Frency (1998) have investigated the problem of handling the assembly line balancing in the clothing industry. Results showed that the GA approach performs much better than the use of a greedy algorithm, which is used by many factories to tackle the assembly line balancing problem. Kuo, Chang, Su, & Fu, (2008) have aimed to find the optimal conditions for dyeing polyester (PET) and Lycra®-blended fabric and predict the quality characteristics, where PET and Lycra®-blended fabric were taken as raw material with dispersed dyes using a one-bath two-section dyeing method, characterizing the color strength of gray fabric. In their experimental design; machine working temperature, dyeing time, dye concentration, and bath ratio, which have an influence on dyeing, were chosen as control factors. It was found that the experimental results that color strength for gray fabric dyed under optimal conditions was closer to the target value. In addition, they constructed a prediction system based on the factors significantly influencing dyeing performance by a integrating genetic algorithm (GA), so as to predict color strength for gray fabric. Hence there is a disadvantage in that it is probable that only local optimal solutions are found instead of global optimal solutions. Wu & Chang (2003) have described the method and procedure for optimizing a textile dyeing manufacturing process in response to the designated waste minimization alternatives, the new environmental regulations, and the limitations of production resources. The optimization steps concerning numerous screening and sequencing combinations of those waste minimization alternatives along the timeline are, therefore, treated as an integral part of the optimal production-planning program under uncertainty. Facing the challenge of dealing with the numerous nonlinear constraints and integer variables in the optimization steps, genetic algorithm is applied as a means in the solution procedure to aid in finding the optimal decision. The case study, illustrated the applicability and suitability of this methodology in a textile dyeing firm. Nurwaha & Wang (2012) have described the application of intelligent control systems in electro-spinning engineering as well as to use these approaches for optimizing processing conditions. A multi-objective optimization method based on gene algorithm (GA) has been proposed for the design and control of electro-spinning process. The processing parameters including Polyvinyl alcohol (PVA) solution concentration, applied voltage, spinning distance and volume flow rate were used as design variables and were mathematically related with the electro-spun fiber properties (fiber diameter and its distribution) using gene expression programming (GEP) technique. Nonlinear mathematical functions were derived based on the processing parameters. Afterward, using a multi-objective optimization technique based on gene algorithm, optimal conditions were found in such a way that, mean electro-spun fiber diameter and its distribution to be minimized. Guo, Wong, Leung, Fan, & Chan (2006) have investigated a multi-objective scheduling problem of the multi- and mixed-model apparel assembly line (MMAAL). A bi-level genetic algorithm was developed to solve the scheduling problem, in which a new chromosome representation is proposed to represent the flexible operation assignment including assigning one operation to multiple workstations as well as assigning multiple operations to one workstation. The proposed algorithm was validated using real-world production data and the experimental results in textile finishing house shown that the proposed algorithm can solve the proposed scheduling problem effectively. Kordoghli, Jmali, Saadallah, & Liouene (2010) have tried to attain inferior cost by optimization of the scheduling of resources in textile finishing plant using genetic algorithms. This work was divided in two steps. In the first one, they studied the times of production process in order to show the difference between the predicted time and the real time of finishing process. In second one, they have set up a program for scheduling jobs using multi-objective genetic algorithm.

The literatures show that genetic algorithm have been applied in different textile process from production of fibers to apparel design and manufacturing. Some studies in the literature are about optimizing textile finishing process and its quality characteristics. This study proposes an experimental design with the multi-objective optimization method, based on a posteriori techniques to innovative textile dyeing and finishing process called color fast finish.

3.0 Experimental Method

Commercially available 100% cotton fabrics, sort no: 1846 (20^s cotton × 20^s cotton 108 × 56 3/1 Drill) and shade: Royal blue. BASF color fast finishing system (PAD N colorants and finishing recipe) was employed as suggested by the BASF manual.

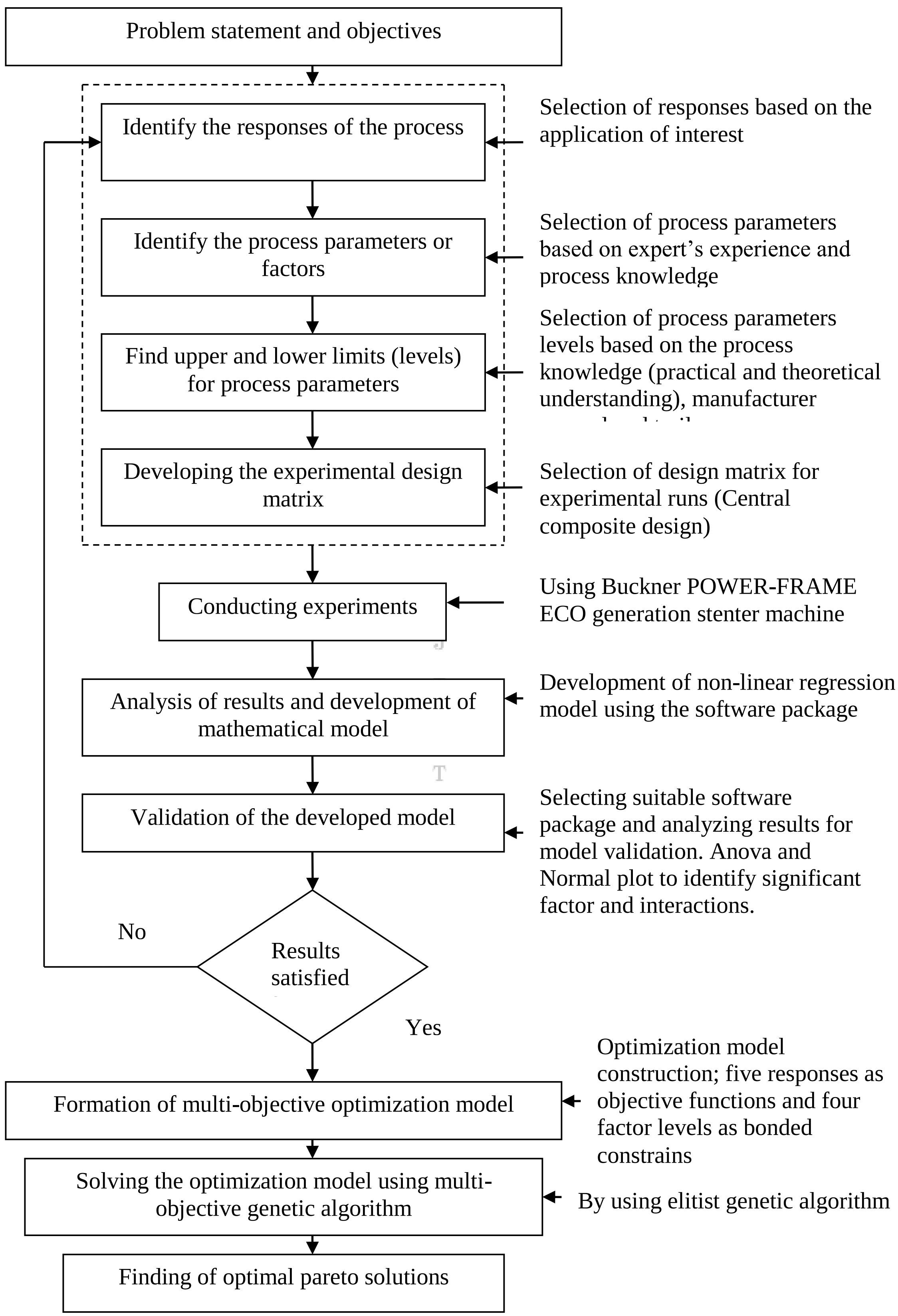


Figure 3. Methodology flow chart

Buckner POWER-FRAME ECO generation stenter machine was used for the color fast finish process. The machine equipped with left, middle and right adjustable squeezing rollers, chemical trough, SPLIT-FLOW hot air circulation system and seven drying chamber with the automatic heat setting feature. Order of mixing of the bath (bath liquor) components (Color fast finish chemicals) is critical and should be poured according to the sequence. The ingredients should not be mixed in their concentrated form. Although the PAD N colorants could be pre-mixed, diluted with water and strained prior to addition. Fabrics to be dyed with the color fast finish system should be properly prepared; they should be dried uniformly before they are padded. Padding is carried out at room temperature on a two bowl padder with left, middle and right adjustment. Padder pressure setting can be varied from 10-70 N / mm. In the two bowl padder, top roll of 65 shore A hardness and bottom roll of 75 shore A hardness will give best results. Padding is carried out at a cloth speed of 5-100 m / min. The bath liquor should be fed continuously from a storage tank so as to maintain a constant level of the trough. Unless the liquor is being re-circulated, it should be stirred in the storage tank with a paddle or mixture every 15-20 minutes. The fabric leaving the padder ideally should be between 40-80% wet pick-up, depending upon the type and construction of the fabric. The fabric should then enter a stenter machine for curing and for obtaining desired width. Curing for 1.5 minutes at $175^{o}C$ is ample. The schematic view of color fast finish process was shown in Figure 2.

4.0 Methodology

The proposed methodology is given as a flow chat (Figure 3), which starts from problem formulation. Then model development phase followed by validation of the model, and multiple objective optimization is given, the proposed systematic approach is as follows:

4.1 Development of Mathematical Model

Five important response functions for color fast finish are shade variation to the standard (CVS), color fastness to washing (CFW), center to selvedge variation (CSV), color fastness to light (CFL) and fabric residual shrinkage (SHR).

Table 1. Responses for color fast finish process

S. No	Responses	Explanation	Standard	Unit of measurement
1	Shade variation to the standard (CVS)	Shade variation of the sample fabric to the standard reference	CIE Lab 1976	ΔE
2	Color fastness to washing (CFW)	Shade change of the sample fabric after detergent washing	AATCC 61	Grey scale
3	Center to selvedge variation (CSV)	Shade variation across the width of the fabric	CIE Lab 1976	ΔE
4	Color fastness to light (CFL)	Shade change of the sample fabric after exposing the sample to sun or xenon light	ISO 105 B02	Blue wool scale
5	Fabric residual shrinkage (SHR)	Fabric shrinkage after detergent washing	ISO 5077 / ISO 6330	mm

Table 1 shows the information about the responses of color fast finish and its measurement system. Selection of the process parameters were based on expert's experience and process knowledge. The selected four factors are temperature of the pre-dryer (T_p), bath liquor pickup (B), machine speed (V) and padder pressure (P). The selection of process parameter's levels was based on the process knowledge (practical and theoretical), manufacturer manual, trail runs, book readings and literature review. In this main experiment plan, Table 2 shows the levels of the four selected factors.

Table 2. Details of factor levels

S. No	**Factors**	**Unit of measurement**	**Star -2 (coded)**	**Low -1 (coded)**	**Centre 0 (coded)**	**High +1 (coded)**	**Star +2 (coded)**
1	Temperature of pre-dryer (T_p)	^oC	450	475	500	525	550
2	Bath liquor pickup (B)	%	40	45	50	55	60
3	Machine speed (V)	m / min	20	25	30	35	40
4	Padder pressure (P)	N / mm	40	45	50	55	60

A central composite design is used to explore the effect of four selected factors. The central composite design of 30 runs is especially useful for finding quadratic effects. This rotatable central composite design was run as 2^4 factorial design, preferably with 6 center points and 6 axial points of star design. The selection of α depend on k, the number of factors being studied. For this four factor design, the value of α is taken as 2 (Box, Hunter, & Hunter, 2005; Cochran, & Cox, 1957). The relationship between the natural value of the factors and coded value of the factors is

$$F_{Nat \to Coded} = \left(\frac{F_{Nat} - F_{Nat\ Center}}{\Delta F} \right);$$

F_{Nat} is the natural (actual) value of a factor, $F_{Nat\ Center}$ is the middle (center) value of a factor and ΔF is the increment value of a factor. The experiments are performed in random order.

The responses investigated were measured as per design layout, averaged and tabulated in Table 3. The results are analyzed using software Design Expert 8.0.

Table 3. Experimental design matrix and results (Central composite design 4^2 with center and start points)

Standard order	**Run order**	**Factors (Coded)**				**Factors (Actual / Natural)**				**Responses**				
		T_p	**B**	**V**	**P**	**T_p**	**B**	**V**	**P**	***CVS***	***CFW***	***CSV***	***CFL***	***SHR***
1	23	-1	-1	-1	-1	475	45	25	45	0.33	3.33	0.17	4.67	14
2	29	1	-1	-1	-1	525	45	25	45	0.61	4.17	0.4	6.33	3
3	6	-1	1	-1	-1	475	55	25	45	0.31	3.33	0.15	5	6
4	7	1	1	-1	-1	525	55	25	45	0.61	3.83	0.39	5.5	7
5	16	-1	-1	1	-1	475	45	35	45	0.35	3.17	0.19	4.33	15
6	15	1	-1	1	-1	525	45	35	45	0.64	3.83	0.41	5.5	6

7	4	-1	1	1	-1	475	55	35	45	0.35	3.67	0.18	5.33	8
8	5	1	1	1	-1	525	55	35	45	0.62	3.67	0.4	5.33	7
9	11	-1	-1	-1	1	475	45	25	55	0.18	3.5	0.05	4.67	10
10	13	1	-1	-1	1	525	45	25	55	0.47	4.17	0.28	6.33	0
11	27	-1	1	-1	1	475	55	25	55	0.24	3.83	0.1	5.67	4
12	17	1	1	-1	1	525	55	25	55	0.52	4	0.32	6	3
13	25	-1	-1	1	1	475	45	35	55	0.3	3.33	0.14	4.5	14
14	21	1	-1	1	1	525	45	35	55	0.56	3.67	0.35	5.83	4
15	3	-1	1	1	1	475	55	35	55	0.35	3.83	0.18	6.83	7
16	10	1	1	1	1	525	55	35	55	0.59	3.83	0.38	6.67	5
17	22	-2	0	0	0	450	50	30	50	0.31	3.83	0.16	6.83	9
18	24	2	0	0	0	550	50	30	50	0.87	4.83	0.6	7.67	0
19	9	0	-2	0	0	500	40	30	50	0.37	2.83	0.2	3.5	10
20	1	0	2	0	0	500	60	30	50	0.42	3.33	0.24	4.33	6
21	14	0	0	-2	0	500	50	20	50	0.33	4.5	0.17	7	5
22	30	0	0	2	0	500	50	40	50	0.46	4.33	0.27	6.67	11
23	28	0	0	0	-2	500	50	30	40	0.44	2.83	0.26	3.67	9
24	19	0	0	0	2	500	50	30	60	0.3	3.17	0.14	4.33	5
25	26	0	0	0	0	500	50	30	50	0.46	4.33	0.27	6.5	12
26	20	0	0	0	0	500	50	30	50	0.46	3.67	0.27	5.5	11
27	12	0	0	0	0	500	50	30	50	0.46	3.83	0.27	5.67	11
28	8	0	0	0	0	500	50	30	50	0.46	3.83	0.27	5.5	11
29	2	0	0	0	0	500	50	30	50	0.46	3.83	0.27	5.5	11
30	18	0	0	0	0	500	50	30	50	0.42	3.83	0.29	5.5	11

* For example standard order 1: CVS 0.33 [(0.28+0.33+0.38)/3]; CFW 3.33 [(3.5 + 3+ ‘3-5~3.5’)/3]; CSV 0.17 [(0.13+0.21+0.17)/3]; CFL 4.67 [(4 + 5 + 5)/3]; SHR 14 [(12 + 14 + 16)/3]

For the response function and for four factors, the selected polynomial could be expressed as:

$$CVS\ or\ CFW\ or\ CVS\ or\ CFL\ or\ SHR\ =\ b_0+b_1(T_p)+b_2(B)+b_3(V)+b_4(P)+b_{12}(T_p\times B)+b_{12}(T_p\times V)+b_{13}(T_p\times P)+ b_{23}(B\times V)+b_{24}(B\times P)+b_{34}(V\times P)+b_{11}(T_p{}^2)+b_{22}(B^2)+b_{33}(V^2)+b_{44}(P^2) \quad (1)$$

All the coefficients of Equation 1 are obtained applying central composite design using the Design Expert 8.0 statistical software package. After determining the coefficients, the final model is developed using these coefficients. The response 'color variation to the standard' of the fabric in actual form [Article no: 1846 (20^s cotton × 20^s cotton 108 × 56 3/1 Drill) and shade: Royal blue] is:

$$CVS\ =\ 7.63-0.05\ T_p+0.05\ B+0.03\ V+0.03\ P-1.50\times10^{-3}\ T_p\times B-4.50\times10^{-5}\ T_p\times V-3.50\times10^{-5}\ Tp\ \times\ P- 2.50\times10^{-5}\ B\ \times\ V+5.25\times10^{-4}\ B\ \times\ P+6.75\times10^{-4}\ V\times\ P+5.52\times10^{-5}\ T_p{}^2-6.21\times10^{-4}\ B^2-6.21\times10^{-4}\ V^2- 8.71\times10^{-4}\ P^2 \quad (2)$$

The actual response models of the other responses are given in the Equation 3 to 6.The Equations are:

$$CFW\ =\ -20.57-0.12\ T_p+1.29\ B-0.24\ V+0.84\ P-1.13\times10^{-3}\ T_p\times B-4.83\times10^{-4}\ T_p\times V-1.63\times10^{-4}\ Tp\ \times\ P+ 2.31\times10^{-3}\ B\ \times\ V+1.86\times10^{-3}\ B\ \times\ P+6.25\times10^{-5}\ V\times\ P+2.02\times10^{-4}\ T_p{}^2-8.72\times10^{-3}\ B^2+ 5.78\times10^{-3}\ V^2-8.62\times10^{-3}\ P^2 \quad (3)$$

$$CSV\ =\ 6.58-0.04\ T_p+0.03\ B+0.02\ V+0.03\ P-2.00\times10^{-6}\ T_p\times B-2.60\times10^{-5}\ T_p\times V-1.80\times10^{-5}\ Tp\ \times\ P+ 3.00\times10^{-5}\ B\ \times\ V+4.7\times10^{-4}\ B\ \times\ P+5.90\times10^{-4}\ V\times\ P+4.31\times10^{-5}\ T_p{}^2-5.22\times10^{-4}\ B^2- 5.22\times10^{-4}\ V^2-7.22\times10^{-4}\ P^2 \quad (4)$$

$$CFL\ =\ -43.13-0.23\ T_p+2.58\ B-0.47\ V+1.73\ P-2.26\times10^{-3}\ T_p\times B-9.65\times10^{-4}\ T_p\times V+3.24\times10^{-4}\ T_p\ \times\ P+ 4.63\times10^{-3}\ B\ \times\ V+3.72\times10^{-3}\ B\ \times\ P+1.25\times10^{-4}\ V\times\ P+4.05\times10^{-4}\ T_p{}^2-0.02\ B^2+ 0.02\ V^2-0.02\ P^2 \quad (5)$$

$$SHR\ =\ -385.63+1.75\ T_p-5.64\ B+2.09\ V+4.06\ P+0.02\times10^{-3}\ T_p\times B-1.24\times10^{-3}\ T_p\times V-1.55\times10^{-3}\ T_p\ \times\ P- 8.14\times10^{-3}\ B\ \times\ V-2.01\times10^{-3}\ B\ \times\ P+0.02\times10^{-3}\ V\times\ P-2.63\times10^{-3}\ T_p{}^2-0.03\ B^2- 0.03\ V^2-0.04\ P^2 \quad (6)$$

Where; T_p, B, V and P are actual levels of the factors. The value for T_p is between 300°C to 500 °C. Similarly the other factor's value is taken from maximum and minimum actual levels. Entire coefficients of Equation 2 are tested for their significance at 95% confidence level applying t-test using Design Expert 8.0 software and Microsoft Excel 2007 package.

Table 4. Significance of coefficients for the response model CVS

Factor	**Coefficients**	**Coefficient estimate**	**df**	**Standard error**	**Lower bound 95% CI**	**Upper bound 95% CI**	***t* - value**	**p > |t|**
Intercept	b_o	7.630000	1	0.0047	7.619919	7.640082	1623.40	< 0.0000
$^*T_p$	**b_1**	-0.050000	1	0.0024	-0.055148	-0.044852	58.87	< 0.0000
$^*B$	**b_2**	0.050000	1	0.0024	0.044852	0.055148	4.42	0.0004

***V**	**b_3**	0.030000	1	0.0024	0.024852	0.035148	13.26	< 0.0000
***P**	**b_4**	0.050000	1	0.0024	0.044852	0.055148	-15.73	< 0.0000
$T_p \times B$	b_{12}	-0.000015	1	0.0029	-0.006235	0.006206	-0.65	0.5252
$T_p \times V$	b_{13}	-0.000045	1	0.0029	-0.006266	0.006176	-1.95	0.0691
$T_p \times P$	b_{14}	-0.000035	1	0.0029	-0.006256	0.006186	-1.52	0.1491
$B \times V$	b_{23}	-0.000025	1	0.0029	-0.006246	0.006196	-0.22	0.8313
***B × P**	**b_{24}**	0.000525	1	0.0029	-0.005696	0.006746	4.55	0.0003
***V × P**	**b_{34}**	0.000675	1	0.0029	-0.005546	0.006896	5.85	< 0.0000
***T_p^2**	**b_{11}**	0.000055	1	0.0022	-0.004664	0.004774	15.64	< 0.0000
***B^2**	**b_{22}**	-0.000621	1	0.0022	-0.005340	0.004098	-7.04	< 0.0000
***V^2**	**b_{33}**	-0.000621	1	0.0022	-0.005340	0.004098	-7.04	< 0.0000
***P^2**	**b_{44}**	-0.000871	1	0.0022	-0.005590	0.003848	-9.87	< 0.0000

* Significant factor coefficients

Table 4 shows the significant coefficients for the response model CVS. The coefficients of the parameters temperature of the pre-dryer (T_p and T_p^2), bath liquor pickup (B and B^2), machine speed (V and V^2), padder pressure (P and P^2) and interactions - (B × P) and (V × P) are significant in t-test. After determining the significant coefficients, the confidence interval and standard error of the Equation 2 are also tabulated. Similarly remaining responses CFW, CSV, CFL and SHR could be studied. Then the model reduction could be possible. The reduced models of color fast finish responses are (at 95% confidence level):

$$CVS = 7.63 - 0.05\,T_p + 0.05\,B + 0.03\,V + 0.03\,P - 5.25\times10^{-4}\,B\times P + 6.75\times10^{-4}\,V\times P + 5.52\times10^{-5}\,T_p^{\,2} - 6.21\times10^{-4}\,B^2 - 6.21\times10^{-4}\,V^2 - 8.71\times10^{-4}\,P^2 \quad (2a)$$

$$CFW = -20.57 - 0.12\,T_p + 1.29\,B - 0.24\,V + 0.84\,P - 1.13\times10^{-3}\,T_p\times B + 2.02\times10^{-4}\,T_p^{\,2} - 8.72\times10^{-3}\,B^2 + 5.78\times10^{-3}\,V^2 - 8.62\times10^{-3}\,P^2 \quad (3a)$$

$$CSV = 6.58 - 0.04\,T_p + 0.03\,B + 0.02\,V + 0.03\,P - 2.60\times10^{-5}\,T_p\times V + 4.7\times10^{-4}\,B\times P + 5.90\times10^{-4}\,V\times P + 4.31\times10^{-5}\,T_p^{\,2} - 5.22\times10^{-4}\,B^2 - 5.22\times10^{-4}\,V^2 - 7.22\times10^{-4}\,P^2 \quad (4a)$$

$$CFL = -43.13 - 0.23\,T_p + 2.58\,B - 0.47\,V + 1.73\,P - 2.26\times10^{-3}\,T_p\times B + 4.05\times10^{-4}\,T_p^{\,2} - 0.02\,B^2 + 0.02\,V^2 - 0.02\,P^2 \quad (5a)$$

$$SHR = -385.63 + 1.75\,T_p - 5.64\,B + 2.09\,V + 4.06\,P + 0.02\times10^{-3}\,T_p\times B + 0.02\times10^{-3}\,V\times P - 2.63\times10^{-3}\,T_p^{\,2} - 0.03\,B^2 - 0.03\,V^2 - 0.04\,P^2 \quad (6a)$$

4.1.1 Model adequacy check

Anova has been used to summarize the test for significance of regression model, test for significance for individual model coefficient and test for lack-of-fit. Summary output revealed that quadratic model is statistically significant for response at the two different conditions. Significant model terms were identified at 95% significance level Goodness of fit was evaluated from R^2 (Coefficient of Correlation) and CV (Coefficient of Variation) in order to check the reliability and precision of the model. Degrees of Freedom (df) mean the number of values that can vary independently of one another. The adequacy of the developed CVS model (Equation 2) was tested using the analysis of variance (anova) technique and the results are given in Table 5.

Table 5. Anova result for CVS (df is degrees of freedom; *F* is Fisher's ratio; *p* is probability)

Source	Sum of squares	df	Mean square	F value	*p*-value (Probability > F)	
Model	0.596821	14	0.04263	319.7276	< 0.0001	significant
$*T_p$	0.462037	1	0.462037	3465.3	< 0.0001	
$*B$	0.002604	1	0.002604	19.53131	0.0005	
$*V$	0.023437	1	0.023437	175.7821	< 0.0001	
$*P$	0.033004	1	0.033004	247.5328	< 0.0001	
$T_p \times B$	5.62×10^{-05}	1	5.62×10^{-05}	0.421868	0.5258	
$T_p \times V$	0.000506	1	0.000506	3.796868	0.0703	
$T_p \times P$	0.000306	1	0.000306	2.296866	0.1504	
$B \times V$	6.25×10^{-06}	1	6.25×10^{-06}	0.046872	0.8315	
$*B \times P$	0.002756	1	0.002756	20.67206	0.0004	
$*V \times P$	0.004556	1	0.004556	34.17215	< 0.0001	
$*T_p^2$	0.032608	1	0.032608	244.5594	< 0.0001	
$*B^2$	0.006607	1	0.006607	49.55508	< 0.0001	
$*V^2$	0.006607	1	0.006607	49.55508	< 0.0001	
$*P^2$	0.013	1	0.013	97.50137	< 0.0001	
Residual	0.002	15	0.000133			
Lack of Fit	0.000667	10	6.67×10^{-05}	0.250008	0.9703	not significant
Pure Error	0.001333	5	0.000267			
Corrected total	0.598821	29				
Std. Dev.	0.011547		R^2	0.99666		
Mean	0.442		Adjusted R^2	0.99354		
C.V. %	2.612438		Predicted R^2	0.990381		
PRESS	0.00576		Adequacy Preci	83.89525		

* Significant factor

The probability > F for the model in (Table 5) is less than 0.05 which indicates that the model is significant, which is desirable as it indicates that the terms in the model have a significant effect on the response. In this case T_p, T_p^2, B, B^2, V, V^2, P, P^2, B × P and V × P are significant model terms. Model fitting with the help of Design-Expert software suggested that a quadratic model provided the best fit, and the model was found to have insignificant lack of fit. This was desirable as we wanted a model that fit. The ANOVA table for the quadratic model indicated that the model was significant at $p < 0.0001$, and it's Lack of fit, 0.97 was not significant. The R^2 value was high, close to one, which was desirable. 95% of R^2 explains that this much percentage of the variability of result. The predicted R^2 value was in reasonable agreement with the adjusted R^2. Adequate precision measures signal to noise ratio was computed by dividing the difference between the maximum predicted response and the minimum predicted response by the average standard deviation of all predicted responses. Ratios greater than 4 are desirable. In this particular case the value was 83.9 which were well above 4, which indicated adequate signals to use this model to navigate the design space. PRESS stands for 'Prediction Error Sum of Squares' and it is a measure of how well the model for the experiment is likely to predict the responses in new experiments. Small values of PRESS are desirable. In this case the value was 0.0058. Similarly significant factors on the responses "color fastness to washing" (CFW), "centre to selvedge variation" (CSV), "color fastness to light" (CFL) and "fabric residual shrinkage" (SHR) could be tabulated and studied. Normal probability plot was a method to find out the significant residual among all the residuals involved in the experiment. The negligible residual effects are normally distributed, with mean 0 and variance σ^2. These effects would tend to fall along a straight line on this plot. Where as significant residual effects would have non zero mean and would not lie along the straight line (Box, Hunter, & Hunter, 2005; Cochran, & Cox, 1957).The normal probability plot of the residuals for shade variation to the standard was shown in Figure 4 reveals that the residuals were falling on a straight line, which means the errors were distributed normally. Similarly for other responses residuals could be studied by plotting their normal probability plots.

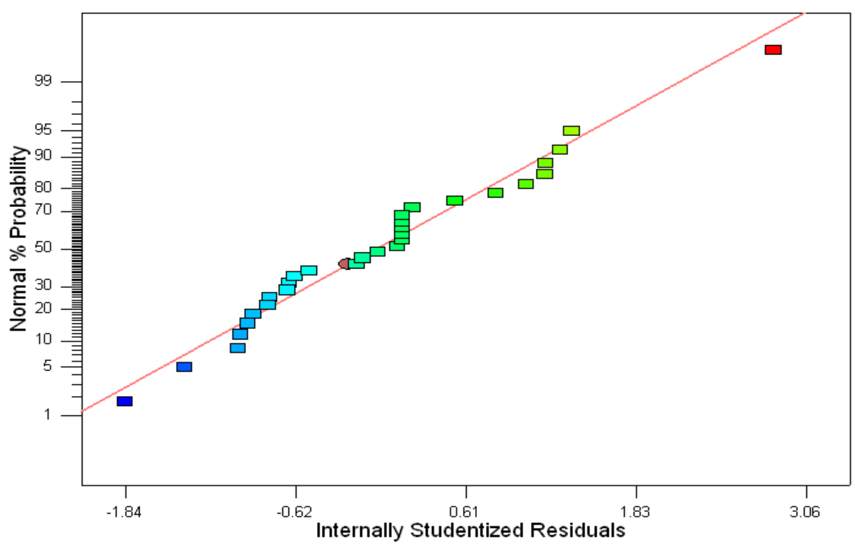
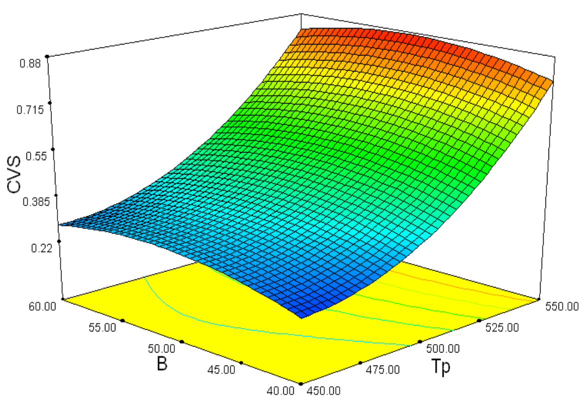


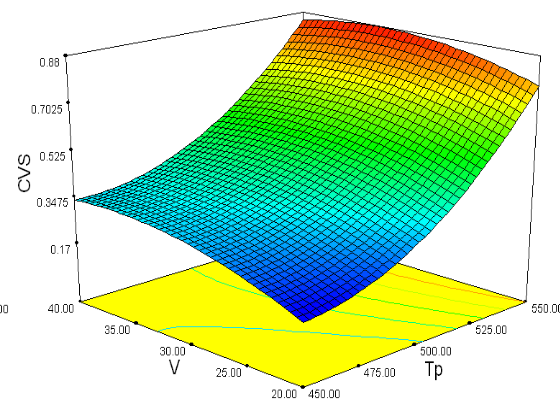
Figure 4. Normal probability plot effects of residuals for CVS

4.2 Response Surface Optimization

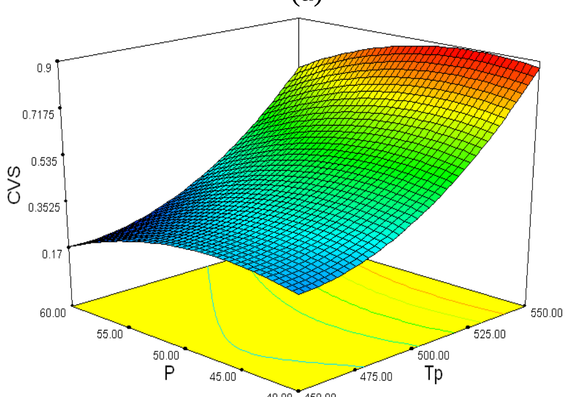
In the present investigation the process parameters corresponding to the minimum CVS is considered as optimum (analyzing the contour graphs and by solving Equation 2). Hence, when these optimized process parameters are used, it will be possible to attain the minimum shade variation to the standard. Figure 5 presents three-dimensional surface plots for the response CVS, obtained from the regression model. The optimum CVS is exhibited by the corners of the response surface plots. Contour plots play a very important role in the study of the response surface analysis, was generated using software Design Expert 8.0. The optimum is identified with reasonable accuracy by characterizing the shape of the surface. If a contour patterning of circular-shaped contours occurs, it tends to suggest independence of factor effects, whereas elliptical contours may indicate factor interactions (Box, Hunter, & Hunter, 2005). Figure 6 (a) to 6 (d) exhibits an almost curved lines and circular-shaped contour, which suggests independence of factor. Where as Figure 6 (e) and 6 (f) shows an almost elliptical contour, which suggests dependence of factors. It is relatively easy to see, by examining the contour plots in Figures 6 (a) to 6 (f), that changes in the shade variation to the standard are more sensitive to changes in temperature of the pre-dryer than to bath liquor pickup, machine speed and padder pressure. When temperature of the pre-dryer is compared with bath liquor pickup at a machine speed 20 m /min and padder pressure 50 N / mm, temperature of the pre-dryer is more sensitive to changes in shade variation to the standard, as illustrated in contour plot Figure 6 (a). Similar effects (high sensitive temperature of the pre-dryer) are observed in Figure 6 (b) and 6 (c). The interaction effect between bath liquor pickup and padder pressure, machine speed and padder pressure is more significant than the interaction effect between other combinations of parameters. Minimum shade variation to the standard is estimated from the response surface and contour plots is 0.0144 ΔE, which is given by the following optimized process parameters: temperature of pre-dryer 475.60 ºC, bath liquor pickup 42.29 %, machine speed 21.85 m / min and padder pressure 57.87 N / mm.



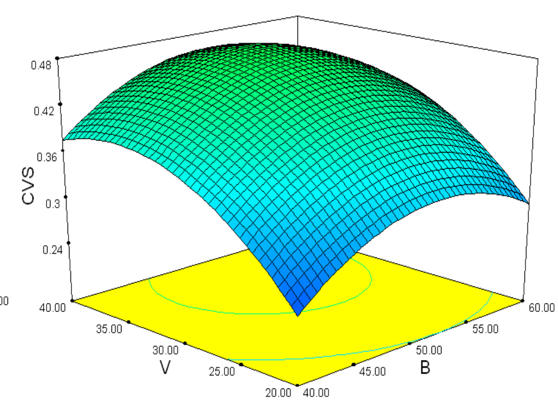
(a)



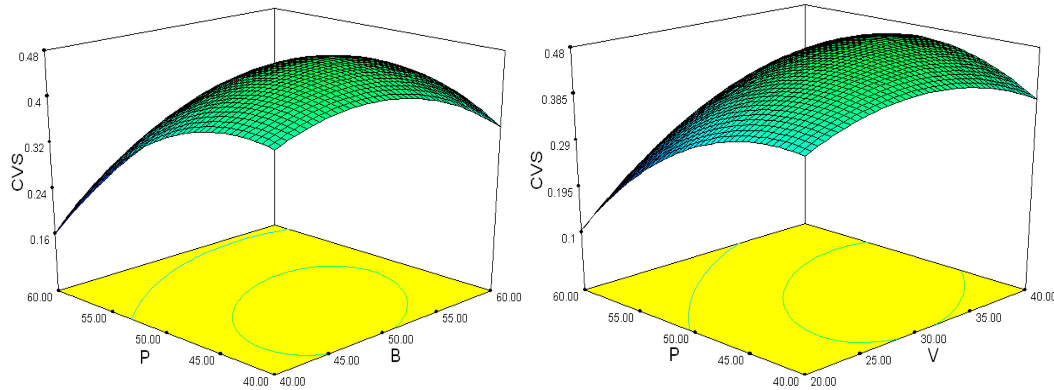
(b)



(c)

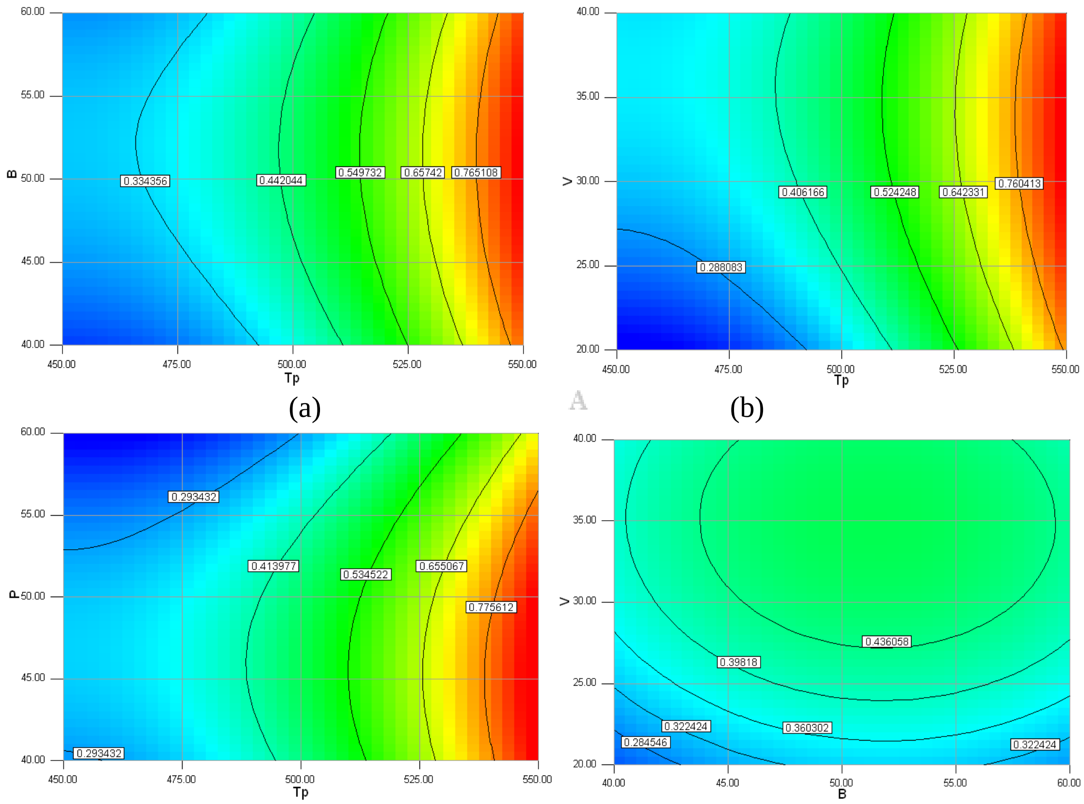


(d)



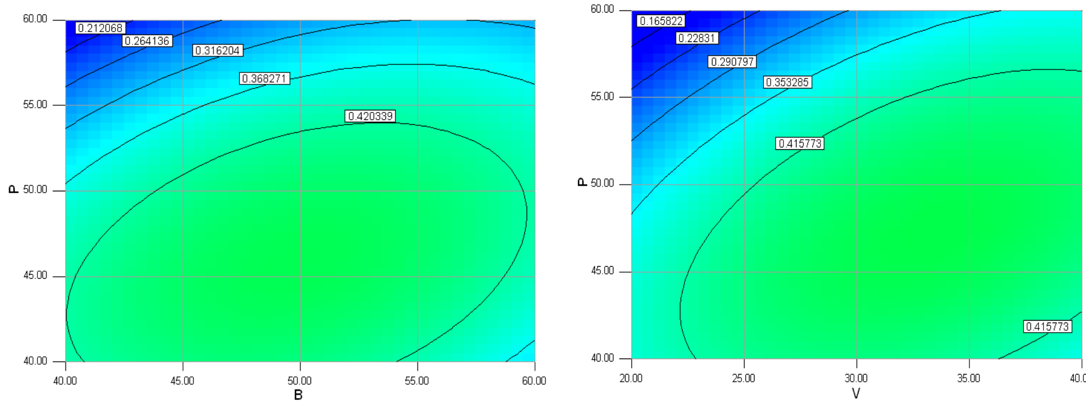
(e) (f)

Figure 5. Surface plots of response CVS against the factor T_p × B, T_p × V, T_p × P, B × V, B × P and V × P



(a) (b)

(c) (d)



(e) (f)

Figure 6. Contour plots of response CVS against the factor T_p × B, T_p × V, T_p × P, B × V, B × P and V × P

The above values were also verified using statistical software Minitab 15. The corresponding optimization plot is depicted in Figure 7. A confirmatory experiment was run using the optimum parameters (listed above) and shade variation to the standard of a sample [1846 (20^s cotton × 20^s cotton 108 × 56 3/1 Drill) and shade: Royal blue] was found to be 0.02 ΔE, which shows excellent agreement with the predicted values. Similarly other responses (CFW, CSV, CFL and SHR) are studied for individual optimized parameter settings and response value. The same was displayed in Table 6.

Table 6. Optimum parameter values of individual responses

Factor / *Response*	Optimum parameter value				Optimum response value
	T_p	B	V	P	
CVS	475.60	42.29	21.85	57.87	0.01
CFW	548.31	44.92	23.07	45.50	5.12
CSV	488.32	41.53	24.48	57.27	3.30×10^{-04}
CFL	540.70	49.12	20.72	49.77	8.67
SHR	525.16	51.19	23.61	56.88	5.86×10^{-07}

But in practical case more responses needs to be considered simultaneously, this kind of sub optimized parameter setting of individual response will not yield optimum results for other parameters.

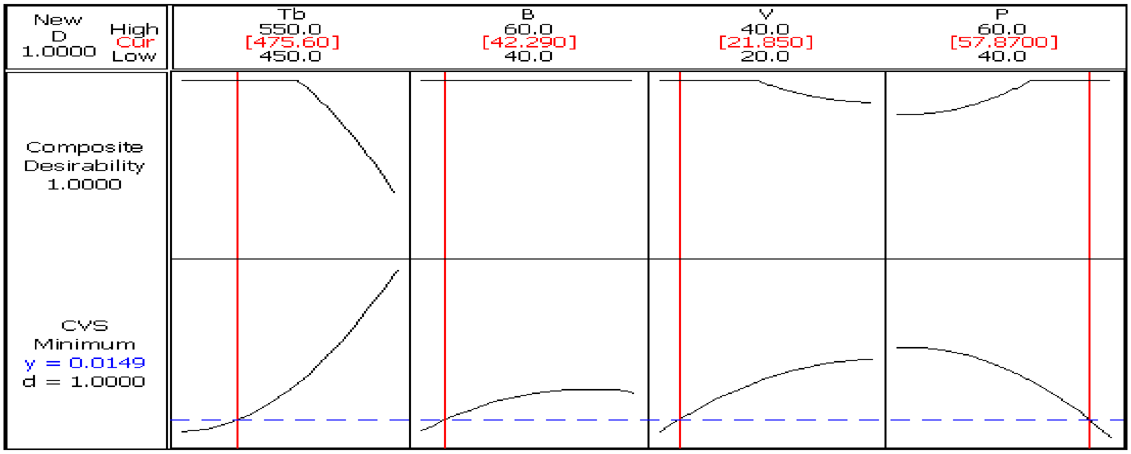


Figure 7. Optimization plot of individual response of CVS

Multi objective optimization deals with solving problems having not only one, but multiple, often conflicting, criteria. Such problems can arise in practically every field of science, engineering and business, and the need for efficient and reliable solution methods is increasing. The task is challenging due to the fact that, instead of a single optimal solution, multi objective optimization results in a number of solutions with different trade-offs among criteria, also known as Pareto optimal or efficient solutions.

4.3 Multi-objective Optimization

Multi-objective optimization is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. For nontrivial multi-objective problems, such as minimizing color variations and maximizing the color fastness, it is difficult to identify a single solution that simultaneously optimizes each objective. While searching for solutions, one reaches points where upon an attempt to improve an objective further deteriorates the second objectives. A tentative solution during such cases is called non-dominated pareto optimal, if it cannot be eliminated by replacing it with another solution which improves an objective without worsening the other. The main objective when setting up and solving a multi-objective optimization problem is to find such non-dominated solutions.

Friedrich, Horobab, & Neumanna (2011) have performed runtime analyses and observed that a fair multi-objective evolutionary algorithm has a marked preference for accepting quick small improvements. This helps to find new solutions close to the current population quicker. Different types of multi objective GA developed for specific purpose differ from each other mainly by using specialized fitness functions and introducing methods to promote solution diversity. An elitist multi-objective GA ensures that the best solution does not deteriorate in the succeeding generations. This approach uses a priority-based encoding scheme for population initialization. Eiben & Smit (2011) have observed that adoption of parameter tuners would enable better evolutionary algorithm design. Using tuning algorithms one can obtain superior parameter values as well as information about problem instances, parameter values, and algorithm performance. This information can serve as empirical evidence to justify design decisions. Lianga & Leung (2011) have integrated GA with adaptive elitist-population strategies for multimodal function optimization. Adaptive Elitist GA is shown to be very efficient and effective in finding multiple solutions of complicated benchmark and real-world multimodal optimization problems. Zio & Bazzo (2011) have proposed a clustering procedure for reducing the number of representative solutions in the

Pareto Front of multi-objective optimization problems. The procedure is then applied to a redundancy allocation problem. The results show that the reduction procedure makes it easier for the decision maker to select the final solution and allows him or her to discuss the outcomes of the optimization process on the basis of his or her assumed preferences. The clustering technique is shown to maintain the Pareto Front shape and relevant characteristics. Su & Hou (2008) have showed that the integrated multi population intelligent GA approach can generate the Pareto-optimal solutions for the decision maker to determine the optimal parameters to assure a stable process and product qualities in the nano-particle milling process. The chief advantage of GA when applied to solve multi-objective optimization problems is the computation of an approximation of the entire Pareto front in a single algorithm run. Thus, considering the advantages of elitist multi-objective GA for solving multi-objective problems, it is applied to optimize the process of color fast finish. In this study, main objective is to find the optimal process parameter settings for the color fast finish responses. The responses; color variation to the standard, centre to selvedge and fabric residual shrinkage are to be minimized. But in the other hand, the responses; color fastness to washing and color fastness to light are to be maximized. The relationship between the process parameters and responses are obtained from response surface methodology (Equations 2 to 6) are taken as objective functions and given in the Equations 7 to 11. The maximum and minimum levels of the factors are taken as upper and lower bound constrains respectively (Equations 12 to 15).

Objective functions:

$$\textit{Minimize} \quad CVS \tag{7}$$

$$\textit{Maximize} \quad CFW \tag{8}$$

$$\textit{Minimize} \quad CSV \tag{9}$$

$$\textit{Maximize} \quad CFL \tag{10}$$

$$\textit{Minimize} \quad SHR \tag{11}$$

Subjected to constrains:

$$300 \leq T_p \leq 500 \tag{12}$$

$$40 \leq B \leq 60 \tag{13}$$

$$20 \leq V \leq 40 \tag{14}$$

$$40 \leq P \leq 60 \tag{15}$$

4.3.1 Genetic algorithm for color fast finish process

GA is run in MATLAB R2012a for generating Pareto optimal solution points for minimizing CVS, CSV and SHR; maximizing CFW and CFL while finishing royal blue on sort no: 1846 (20^s cotton × 20^s cotton 108 × 56 3/1 Drill). Equations 7 to 11 are used for creating the fitness function of the multi objective optimization and it is written in a 'M' file. During the formulation of fitness functions; both the maximization objectives (CFW and CFL) are converted to minimization objectives by multiplying a negative unity. The range of the process parameters (Equations 12 to 15) is placed as bounds on the four input control variables and the algorithm options are set in the Table 7.

Table 7. Genetic Algorithm Parameters

Population type	Double vector
Population size	100, 150, 200 and 300
Selection function	Tournament size 2
Crossover fraction	0.8
Crossover function	Scattered
Mutation function	Adaptive feasible
Direction of migration	Forward with migration function 0.2
Distance measure function	Distance crowding
Pareto front population fraction	0.35
Stopping criteria generations	Over 500

The variant of GA used to solve this multi-objective optimization problem is a controlled elitist genetic algorithm (a variant of NSGA-II). Elitist GA favors individuals with better fitness value. A controlled elitist GA maintains the diversity of population for convergence to an optimal pareto front. Weighted average change in the fitness function value over 500 (200 × number of decision variables) generations is used as the criteria for stopping the algorithm. The initial population size is varied as 100, 150, 200 and 300 for improving the solution of the problem, then the optimized pareto front achieved after 124, 103, 173 and 211 iterations are shown in Figure 8. In Figure 8, the two conflicting responses of minimizing color variation to the standard and color fastness to washing are marked along *x*-axis and *y*-axis respectively. The individual star marks between these axes depict individual non dominated solution point among the pareto optimal set of all the star points which form the pareto front. The number of pareto solutions is getting increased from Figure 8 (a) to 8 (d) substantially. This is because of increase in population size. Similarly other response combinations of pareto front can be studied. Input control parameters corresponding to the selected pareto optimal set of solutions are tabulated in Table 8.

Table 8. GA predicted results of color fast finish

	Parameters				Responses				
S.No	**T_p**	**B**	**V**	**P**	**CVS**	**CFW**	**CSV**	**CFL**	**SHR**
				Population size 100					
1	484.80	45.62	20.18	52.50	0.19	-4.12	0.06	-6.23	6.53
2	530.77	45.52	20.05	55.87	0.42	-4.85	0.23	-7.70	-6.05
3	525.45	41.05	20.17	56.17	0.30	-4.23	0.14	-6.47	-7.73
4	530.13	42.81	20.11	56.28	0.37	-4.58	0.19	-7.17	-8.20
5	521.28	45.57	20.03	58.11	0.27	-4.33	0.11	-6.66	-5.28
6	488.82	46.09	20.17	51.98	0.22	-4.22	0.09	-6.44	6.36
				Population size 150					
1	538.79	45.23	20.08	55.69	0.50	-5.10	0.29	-8.21	-9.00
2	451.12	52.27	19.98	51.75	0.33	-4.54	0.17	-7.07	8.07
3	532.66	45.13	20.07	55.85	0.43	-4.89	0.24	-7.77	-6.95
4	490.30	45.69	20.09	54.24	0.17	-4.12	0.05	-6.23	4.71
5	491.07	46.10	20.08	52.70	0.22	-4.24	0.08	-6.48	5.62
6	461.06	53.08	39.86	54.56	0.34	-4.57	0.17	-7.14	7.20
7	483.50	47.28	20.38	52.82	0.20	-4.20	0.06	-6.39	6.27
				Population size 200					
1	484.02	45.48	20.12	52.47	0.18	-4.10	0.06	-6.20	6.58
2	519.99	43.55	20.17	57.43	0.26	-4.21	0.10	-6.41	-5.15
3	500.57	45.01	20.11	54.06	0.23	-4.23	0.09	-6.46	3.24
4	452.05	52.82	20.18	51.70	0.19	-4.12	0.07	-6.25	7.15
5	525.01	43.06	20.03	54.54	0.37	-4.63	0.20	-7.25	-4.68
6	526.27	42.05	20.08	58.52	0.25	-4.09	0.09	-6.18	-9.69
7	508.47	44.33	20.10	52.07	0.32	-4.43	0.16	-6.86	2.67
8	493.49	45.03	20.17	54.42	0.18	-4.08	0.05	-6.16	4.23
				Population size 300					
1	475.44	46.81	20.02	51.70	0.18	-4.17	0.05	-6.35	7.01
2	476.48	47.24	20.27	51.26	0.19	-4.19	0.07	-6.37	7.27
3	481.40	46.45	20.02	52.02	0.19	-4.18	0.06	-6.37	6.74
4	519.49	44.49	20.14	56.13	0.30	-4.43	0.14	-6.86	-3.23

5	529.41	43.76	20.12	58.47	0.30	-4.36	0.14	-6.73	-9.42
6	520.85	42.60	20.10	56.25	0.28	-4.28	0.13	-6.56	-4.97
7	534.27	42.34	20.04	53.76	0.47	-4.92	0.27	-7.83	-8.20
8	500.94	46.64	20.02	50.58	0.31	-4.47	0.16	-6.95	5.35
9	451.09	51.51	20.17	52.67	0.15	-4.09	0.03	-6.18	0.08
10	510.75	41.64	20.02	53.79	0.26	-4.12	0.11	-6.23	-0.39

These pareto optimal solutions are filtered from the original pareto front (Figure 5) based on the requirement of the response. The requirements are given as follows. The response CVS is taken for consideration if it is less than 0.75 ΔE. In case of CFW, the minimum allowed value is grey scale 4. While considering the response CSV, the maximum limit is 0.3. For the response CFL, the minimum value of grey scale 4 is considered. A tolerance of ± 10mm is considered for the response SHR. From the Table 8, it is observed that an improvement in minimizing color variation to the standard deteriorates the quality of color fastness to washing and vice versa. Thus, each solution point is a unique non dominated solution point. Similar inferences were observed also in the other response combination.

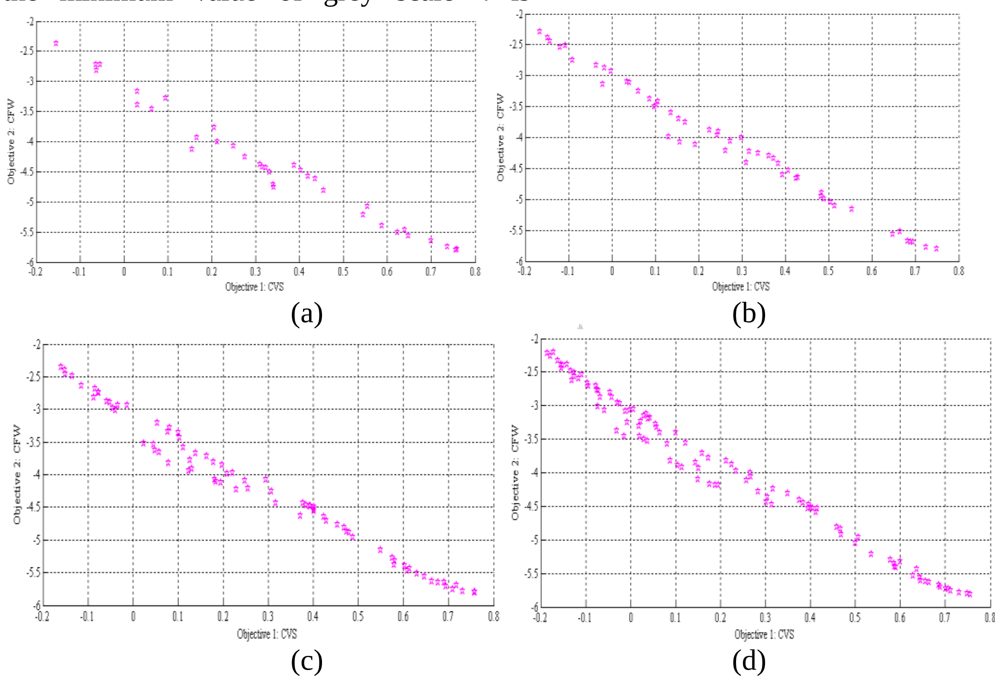


Figure 8. Pareto-optimal set of solutions obtained for responses CVS and CFW at population size 100, 150, 200 and 300

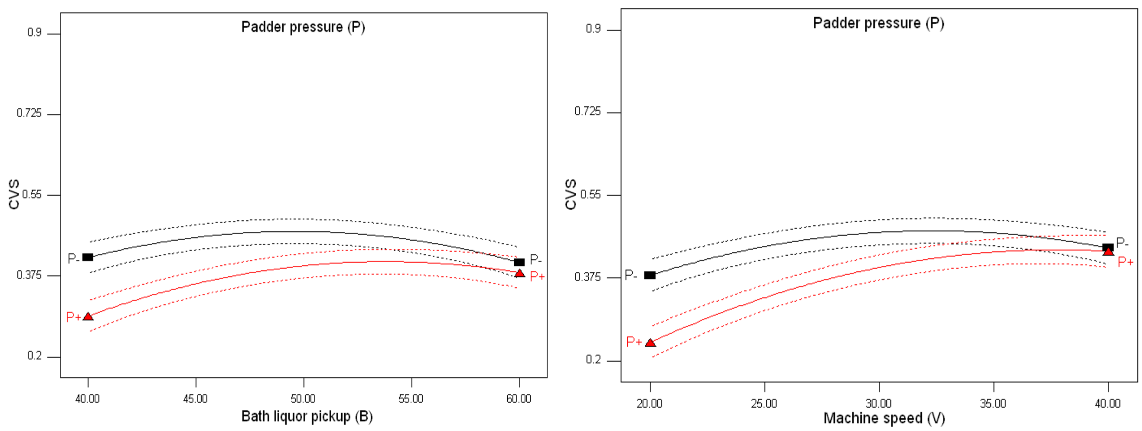
5.0 Results

Central composite design is an efficient way, with a minimal number of runs, of determining the important factors and its quadratic effects. They may also be used as a first step when the ultimate goal is to model a response with a response surface. In this experimental design, four factors were studied. The experiments were conducted according to the layout of rotatable central composite design of 2^4 factorial design, preferably with 6 center points and 6 axial points and five response functions values are obtained then averaged. An empirical relationship was developed to predict the responses (CVS, CFW, CSV, CFL and SHR) of color fast finish on Article no: 1846 (20^s cotton × 20^s cotton 108 × 56 3/1 Drill) and shade: Royal blue at the 95 percent confidence level, incorporating color fast finish process parameters. From the estimates of anova, normal probability plots and *t*-test the significance of all the factors effects, quadratic effects and interaction effects are ensured. Then the optimization mode was made; objective function as the relationship between the process parameters and responses which have been obtained from response surface methodology. The maximum and minimum levels of the factors are taken as upper and lower bound constrains respectively. A multi-objective optimization using genetic algorithm (GA) is proposed to obtain the optimal parameters in color fast finish processes. GA is run in MATLAB R2012a for generating Pareto optimal solution points. The solution obtained from GA is a set of pareto optimal points (Figure 5) where each point is non dominated. The observed responses were obtained in a single process parametric combination setting. Table 6 records the range of values for responses at different parametric combination with four different population size. From this pareto front based multi objective optimization, the following optimal parameters values are selected from the list of solution: temperature of the pre-dryer (T_p) 451.1 ºC, bath liquor pickup (B) 51.51 %, machine speed (V) 20.17 m / min and padder pressure (P) 52.67 N / mm. The multiple responses value for the optimized conditions are: shade variation to the standard (CVS) 0.15 ΔE, color fastness to washing (CFW) 4.09 grey scale, center to selvedge variation (CSV) 0.03 ΔE, color fastness to light (CFL) 6.18 blue wool scale and fabric residual shrinkage (SHR) 0.08 mm. It is observed that an increase in population size will increase in number of pareto optimal solution. If the pareto optimal solution increases then the solution space would be explored more and deep. If we increase the population size further besides the time constrains, still more optimum results are possible. From the response values as listed in Table 8, it is understood that an improvement in minimizing center to selvedge variation deteriorates the quality of fabric residual shrinkage and vice versa. Thus, each solution point is a unique non dominated solution point. Therefore, instead of a single solution point, a set of solution points are predicted for simultaneously optimizing both the responses. A change in the value of any one of the considered control parameters further improves any one of the responses at the cost of degrading the second response. In real life situations, as in this case of multi-objective optimization of color fast finish process, the responses are often conflict with each other. At such situations it is often difficult and at times impossible to predict a single solution point that optimizes all the responses simultaneously. Pareto optimal set of solution provides a novel approach for solving such problems. This result is helpful as it provides a wide range of optimal setting of control parameters for simultaneously optimizing both the responses. Hence, flexibility in the operation of the machine is achieved by presenting different parametric combinations for the range of predetermined desired responses.

6.0 Discussion

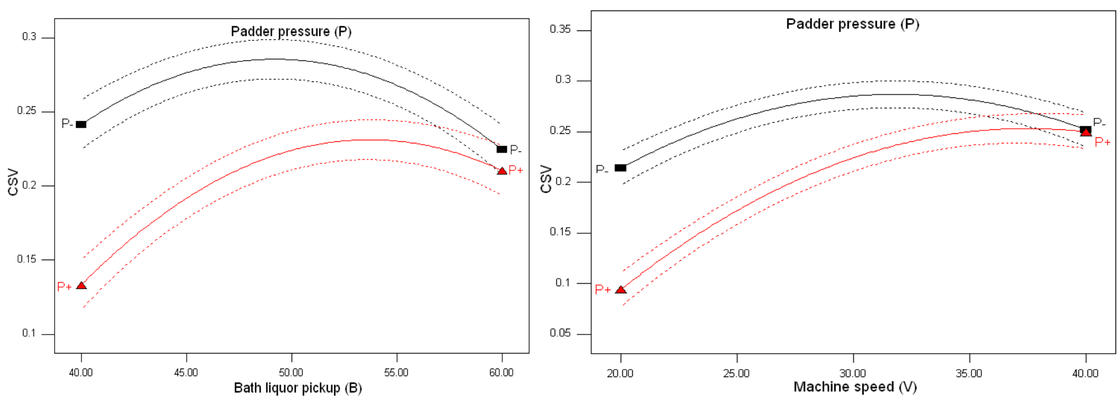
[1] In the color fast finish process, padder pressure decides the penetration level of color fast finish size into the core of the fabric to be finished. The optimum value of the padder pressure is 52.67 N / mm as per the optimization algorithm. More the padder pressure of stenter machine mangle; more the penetration takes place and vice versa. More penetration will bring the better color build-up to the fabric being dyed. If the penetration is less then 'core of the yarn' of the fabric will not be dyed completely. Bath liquor pickup decides the application of required color fast finish size (inclusive of PAD N colorants and resins) to the fabric being dyed. More bath liquor pickup will yield to application of more color fast finish size to the fabric and vice versa. The lower padder pressure and more bath liquor pickup combine to cause poor core penetration of the CFF size and poor add on. The excessive impenetrate CFF size on the fabric surface will lead to unevenness in the dyeing. This combination results in poor shade build-up and causing more color variation compare to the standard. On the other hand, higher padder pressure

and lesser bath liquor pickup combine to cause better core penetration, better add on and no excessive size on the fabric surface. This condition results in better shade build-up and causing minimized color variation compare to the standard and this evident from Figure 9 (a). Similar reasons could be explained for Figure 10 (a), higher padder pressure and lesser bath liquor pickup combine to cause minimized center to selvedge variation.



(a) (b)

Figure 9. Interaction between the factors (B × P) and (V × P) on response CVS

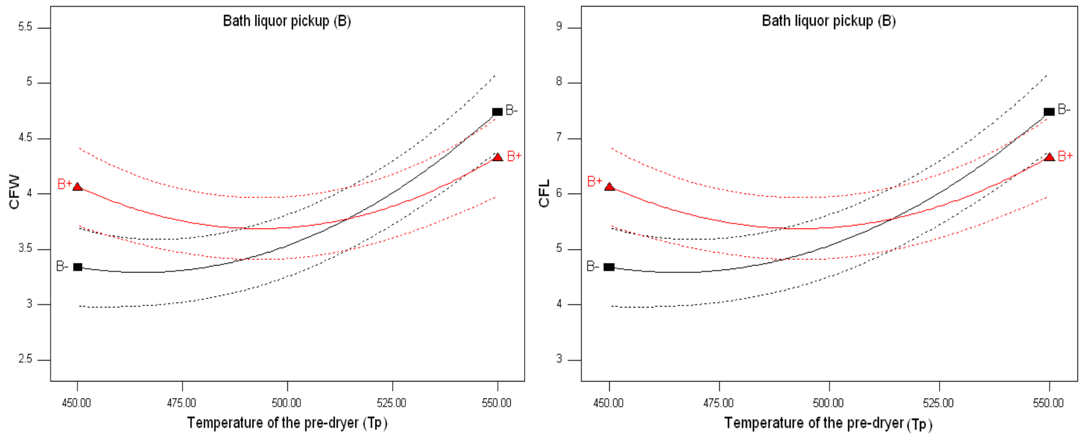


(a) (b)

Figure 10. Interaction between the factors (B × P) and (V × P) on response CSV

[2] Machine speed is another important parameter of color fast finish process, this will lead to ensure the required setting time of the color fast finish process. The optimum value of the machine speed suggested by the optimization algorithm is 20.17 m / min. Higher the machine speed of stenter machine; lesser the setting time and vice versa. If the setting time is lower then color fixation will be poor and results poor shade build-up. If the setting time is higher then it will provide good color fixation, proper setting and excellent shade build-up. The higher machine speed and lower padder pressure combine to cause poor core penetration and improper setting of PAD N colorants. This combination results in poor shade build-up and causing more color variation compare to the standard. On the other hand, lower machine speed and higher padder pressure combine to cause good core penetration and complete setting of the fabric. This condition results in good shade build-up and causing minimized color variation compare to the standard and this is clearly evident in Figure 9 (b). The same reasons could be applicable

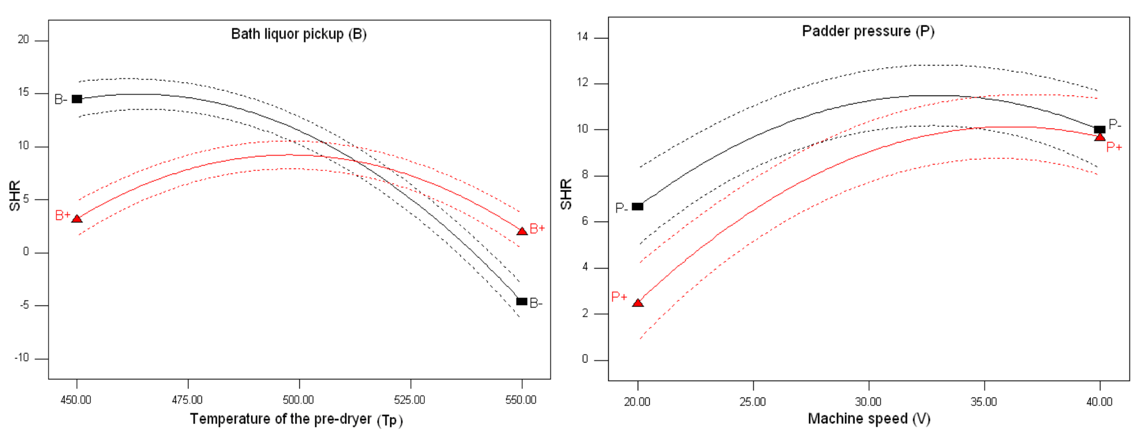
for Figure 10 (b), lower machine speed and higher padder pressure combine to cause minimized center to selvedge variation.



(a) (b)

Figure 11. Interaction between the factors (T_p × B) on response CFW and (T_p × B) on response CFL

[3] Temperature of the pre-dryer is a significant parameter to the color fast finish process that will pre heat the fabric to avoid the migration of the PAD N colorants, but it will cause pre setting of color fast finish size and affect the required shade build-up. The multi-objective genetic algorithm yields the optimum value of the temperature of the pre-dryer, which is 451.1 ºC. Higher the temperature of the pre-dryer; lower the migration effect with good pre setting effect and vice versa. The lower temperature of the pre-dryer and higher bath liquor pickup combine to cause migration effect, poor pre setting of the fabric and more moisture of the fabric. This combination results in poor setting of the fabric and causing low color fastness to washing. On the other hand, higher temperature of the pre-dryer and lower bath liquor pickup combine to cause complete setting of the fabric. This condition results in maximum color fastness to washing and this is clearly evident in Figure 11 (a). The same reasons could be applicable for Figure 11 (b), higher temperature of the pre-dryer and lower bath liquor pickup combine to cause maximum color fastness to light.



(a) (b)

Figure 12. Interaction between the factors (T_p × B) and (V × P) on response SHR

[4] In the color fast finish process, bath liquor pickup decides the application required color fast finish size (inclusive of PAD N colorants and resins). Bath liquor pickup 51.51 % is the optimum value obtained from the optimization results. More the bath liquor pickup; more the application of color fast finish size on the fabric and vice versa. Color fast finish size contains resin component. Resins are anti-shrinking agent. This will bring the fabric residual shrinkage under control. The higher bath liquor pickup and reduction in the temperature of the pre-dryer combine to cause increase cross linking between the fibers of the fabric. At very low temperature of the pre-dryer, excess cross linking occurs and fabric becomes very brittle. This combination results in low fabric residual shrinkage value or elongation of the fabric after washing. On the other hand, lower bath liquor pickup and increase in the temperature of the pre-dryer combine to cause higher degree of linkage between the fibers of the fabric. At very high temperature of the pre-dryer, excess cross linking occurs and fabric becomes very brittle. So both of these condition results in excess shrinkage fabric residual shrinkage and clearly seen from Figure 12 (a). The lower machine speed and higher padder pressure combine to cause good core penetration of resin and complete setting of the fabric. This condition results in good cross linking between the fibers of the fabric and causing perfect shrinkage controlled fabric (either shrink, or elongation) and this is clearly evident in Figure 12 (b).

7.0 Conclusions

In this paper, the application of response surface methodology from the point of view of color fast finish is discussed. The methodology integrates process modeling, employed to fit an appropriate models from experimental data, regression analysis and multi-objective optimization. The developed model is limited with its boundary conditions and is non-transferable. This means that it is only valid for the considered color fast finish recipe and its experimental setup combination. The development of response surface model has been founded on central composite design of experiments with five factor levels. The run size of the central composite design is not so large that it would incur unnecessary experimental expenses. Moreover, the design allows sequential model development of increasing order, an estimate of experimental error and relative insensitivity to errors in control of design levels. Consistent testing for model (Table 5) lack of fit has been pointed out in a very least value, because it would require more real experimental replicates, which are not just repeated measurements. The replicates on the response at the particular experimental run are useful and have to be included in experimentation. The developed full model includes some interaction terms that are not significant. Advanced modeling would, therefore include model reduction and elimination of terms that are not significant in the way that statistical hierarchy is not violated. The model reduction is either step-wise or it follows backward or forward elimination. The analysis of variance proved that the temperature of the pre-dryer most significantly affects the color variation to the standard. The color variation to the standard is additionally affected by the machine speed, bath liquor pickup and the padder pressure. This was not the case in conventional dyeing, where the time, pH and temperature factors predominate. The experimental optimization of the response surface model is an iterative process. The experiments conducted in one set of experiments result in fitted model that indicate where to search for improved operating conditions in the next set of experiments. Thus, the coefficients in the fitted model may change during the optimization process. The response model contains random variability due to uncontrollable or unknown complexities. This implies that an experiment, if repeated more, will result in a different fitted response surface model that might lead to different optimal operating conditions. The presented approach solved the optimization problem in a perfect way; hence it is appropriate for application. Moreover, multi-objective genetic algorithm techniques are very convenient for simple multi-objective optimization to more complicated multi-objective optimization (more than three objectives), which is necessary for further process improvement. In this way the physical quality characteristics, color matching recipe and environmental benefits have to be included in the optimization problem formulation and our future research activities. This is especially important in color fast finish process. Since this experimental study is a more generic procedure, it could be deployed to the other value chain of the textile process. The value chain elements: ginning, spinning, sizing, weaving, knitting and garmenting are suitable to implement optimized process by considering more than one objective simultaneously. But care should be given to the process responses and process parameters selection according the field of interest. For spinning operation: twist, linear density of yarn and elongation of yarn are the some of the process parameters which could be classified for the response tensile strength of yarn. The expert team of people should select the performance attributes. The similarly it can be applied to other elements of textile value chain The current study will help the textile company's research & development managers, Industrial engineers, quality mangers and dyers to capture the optimized and robust process conditions to achieve the quality output.

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