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Reducing Variation of Dyeing Process in Textile Manufacturing Industry

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***Abstract*—**This study deals with a multi-criteria optimization problem which has been transformed into a single objective optimization problem using Response Surface Methodology (RSM), Artificial Neural Network (ANN) and Grey Relational Analyses (GRA) approach. Grey-RSM and Grey-ANN are hybrid techniques which can be used for solving multi-criteria optimization problem. There have been two main purposes of this research as follows.

1. To determine optimum and robust fiber dyeing process conditions by using RSM and ANN based on GRA,
2. To obtain the best suitable model by comparing models developed by different methodologies.

The design variables for fiber dyeing process in textile are temperature, time, softener, anti-static, material quantity, pH, retarder, and dispergator. The quality characteristics to be evaluated are nominal color consistency of fiber, maximum strength of fiber, minimum color of dyeing solution. GRA-RSM with exact level value, GRA-RSM with interval level value and GRA-ANN models were compared based on GRA output value and MSE (Mean Square Error) performance measurement of outputs with each other. As a result, GRA-ANN with interval value model seems to be suitable reducing the variation of dyeing process for GRA output value of the model.

***Keywords*—**Artificial Neural Network, Grey Relational Analysis, Optimization, Response Surface Methodology

I. INTRODUCTION

IN the area of textiles, the most widely employed method of applying colors is dying. Although dyeing process affected by many inside and outside parameters is a mature technology during several thousand years, it is still complicated today to fully understand and control dyeing which is more an art than a science. Besides, it is difficult to monitor but must be dealt with to obtain quality products [1].

There have been some studies in the literature about improving dyeing process quality characteristics. Kuo and Pietras [1] proposed a regression-based new approach to pH control in open beck dyeing to improve its process quality. Ravikumar *et al.* [2] successfully employed 2^4 full factorial central composite designs for experimental design and analysis of the results. The combined effect of pH, temperature, particle size and time on the dye adsorption was investigated and optimized using Response Surface Methodology (RSM). Kuo *et al.* [3] 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. Hench and Al-ghanim [4] presented a two-phase approach to the development of neural network architecture to determine the underlying function that governs the dyeing process. Köksal [5] developed a methodology for robust design of the batch dyeing process. Kuo and Fang [6] applied the Taguchi method to find the optimal dyeing processing parameters within least number of experiments for achieving the color required on the raw fabrics. Modeling and fuzzy control of pH in exhaust dyeing was studied by Jahmeerbacus *et al.* [7]. The main aim of this study is to provide the improvement of the product (acrylic fiber) quality so that desired (nominal) color strength, maximized acrylic fiber strength and minimized dyestuff on dye bath as three quality characteristics can be achieved by improving process conditions at dyeing process. Therefore, life of carpet that is the final product of factory will get longer. As a result, customer satisfaction will increase. The suggested methodology is to enhance the quality of the dyed acrylic fiber, reduce defective products and provide the dyeing operations much more efficient. All of these translate into significant cost savings. In this study, we formed RSM orthogonal matrix, then, three quality characteristic used were combined with GRA, so performance index was existed. In order to be able to perform all analysis depending on RSM and ANN, STATISTICA software version 9.0 was employed. Optimal dyeing process parameters were determined with hybrid Grey-RSM exact, interval, and Grey-ANN approaches. After weighting of three quality characteristics, grey relational grade was used to reduce the number of quality characteristics as combined performance criteria. Thus, we measured and evaluated the process performance based on the combined criteria. All RSM experiments were made in the laboratory of Textile Factory and Erciyes University in Turkey. Fiber dyeing production was performed in Factory as reality in optimal process conditions determined. Process flow chart for dyeing process is shown in Fig. 1.

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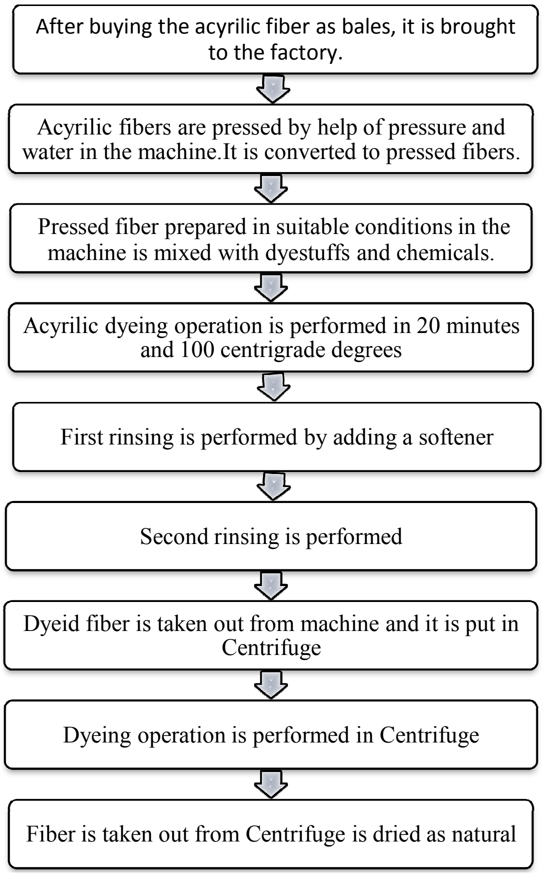

After buying the acyrilic fiber as bales, it is brought to the factory.

Acyrilic fibers are pressed by help of pressure and water in the machine.It is converted to pressed fibers.

Pressed fiber prepared in suitable conditions in the machine is mixed with dyestuffs and chemicals.

Acyrilic dyeing operation is performed in 20 minutes and 100 centrigrade degrees

First rinsing is performed by adding a softener

Second rinsing is performed

Dyeid fiber is taken out from machine and it is put in Centrifuge

Dyeing operation is performed in Centrifuge

Fiber is taken out from Centrifuge is dried as natural

Fig. 1 Acrylic fiber dying process in the factory

II. DESIGN OF EXPERIMENT

Factors having an effect on quality characteristics at the time of making of dyeing experiments were determined as temperature, time, rinsing, anti-static, material quantity, pH, retarder, and dispergator. There have been three quality characteristics consisting of color consistency of fiber, strength of fiber, and color of dyeing solution as process outputs. In dyeing process, we take eight process inputs into consideration (see Table I). Input factors (parameters) consisting of process temperature, process time, softener, anti-static, material quantity, pH, retarder, and dispergator which have an influence on dyeing, were chosen as control factors. Quality characteristics are important outputs that measure the performance of dyeing process. Color consistency of fiber must be nominal, acrylic fiber strength should be maximized and dyestuff on dye bath (color of dyeing solution) should be minimized. Color consistency of fiber is the color value obtained after dyeing and it must be closer to 33.43 (K/S) nominal value for minimizing variation between different lots. Strength of fiber is based on the dyestuff and chemicals having an effect on the strength of fibers. It is used during the dyeing process. Because of this fact, strength tests of dyed acrylic fibers were done. If color of dyeing solution is darker than the expected, it shows that the amount of unnecessary dyestuff was used during dyeing process. Hence, resting dyestuff in the solution is tried to minimize in the process to detect optimal process conditions. The selected fiber is acrylic discrete fiber used in carpet production and the dyestuff used for dyeing is basic (cationic) dyestuff. RSM technique for optimum dyeing parameter design was employed to conduct experiments using RSM orthogonal arrays and analysis of variance was incorporated to determine optimal processing conditions, significant factors, and percent contribution. We considered RSM-82 orthogonal array for experiments in three levels to analyze the process.

TABLE I
QUALITY CHARACTERISTICS

Symbol	Factors	Unit	Level -1	Level 0	Level 1
A	Temperature	˚C	80	90	100
B	Duration	Minute	20	30	40
C	Softener	Type	A	B	C
D	Anti-static	Type	A	B	C
E	Material quantity	Gram	3	5	7
F	pH	-	4.5	5	5.5
G	Retarder	ml	0.15	0.20	0.25
H	Dispergator	ml	0.15	0.20	0.25

A. Independent Variables (Factors)

One of the most important parameters in fiber dyeing process is temperature. The reason for selection as parameter of temperature is that acrylic fiber has a polymer structure and dye taking amount with temperature, thus, fiber color value (K/S) increases [8]. Acrylic fibers, depending on high crystallization, don’t absorb dyestuff until a defined temperature. Sudden absorption occurs above this defined temperature. Temperature which changes structure of acrylic molecules as 79.58 ˚C is called “glass transition temperature” [9]. Below the glass transition temperature (Tg) of the acrylic fiber (about 70°-90° C.), the rate of dyeing is extremely low. After 80˚C that is glass transition temperature of acrylic fiber, dyeing process starts at this temperature. Above this temperature the rate of dyeing becomes extremely fast such that an increase of only several degrees in temperature can double the rate of dyeing. Because of polymer structure, maximum temperature applied to dyeing of acrylic fiber is 100°C. The dyeing of acrylic fiber is generally done at a temperature below about 110°C to avoid fiber damage.

Fixation duration on the fiber surface of dyestuff at fixed temperature is important the reason for taking dyestuff. It is between 20 minutes which is minimum duration for taking dyestuff and 40 minutes which slows down dyestuff taking amount after this duration [10].

As raw material of acrylic is a man-made fiber, it is susceptibility for static induction to proceed from friction. This situation affects working performance in yarn processes directly. Anti-static chemical materials prevent static-induction by forming a protective layer on the fiber surface and improve working performance. Levels consist of A (currently used), B (previously used), C (unused until now) different trade marks in terms of various chemical structures.

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Based on application performed in dyeing process of factory, there seems to have been color tone (shade) differentiation between running at full capacity and a determined capacity rate of machines. Because of this situation, the amount of acrylic material is selected as parameter. As surface area widens, the amount of material decreases and dye absorption amount increases [2]. In the measurement of fiber amount, it was determined that the minimum amount of dyeing and test operations to be performed is 3 gram. Besides, the maximum capacity of dyeing flask used in laboratory is 7 gram.

These chemicals have lubricant properties and are electrically conductive, thus making the fibers feel smoother and preventing build up of static electricity. Other functions are improvements of iron glide during ironing, increased resistance to stains, and reduction of wrinkling and pilling. For these reasons, better strength structure will be obtained against tension in yarn manufacturing process. Thus, softener affects the strength of fiber. Depending on the experience of factory, chemical contents are more significant than the amount of softener. We selected three softener, namely, A (currently used), B (previously used), and C (unused until now).

pH is defined as the negative logarithm of the hydrogen ion concentration. pH plays a crucial role in successful dyeings since dyes and fibers interact differently in baths of different degrees of acidity or alkalinity. Not only it regulates dye adsorption and color yield, but it also impacts the health of the dyed goods. If the pH is not correct at the start of the dyeing cycle, a number of defects can arise including poor fixation, unevenness, and wastage of dyestuffs [1]. The importance of pH, which is an indicator of the acidity or alkalinity of a liquid, is manifested by the fact that textile fibers bond more tightly with dyes and last longer if they are processed in appropriate liquors. Evenness of dyeing may also be improved by adjusting the temperature profile or changing the pH of the dye liquor to control the strike rates. Some types of dye molecules are prone to color degradation, precipitation and destruction. Therefore, pH in the range 4–5.5 is recommended as the dye pH for functional acrylic fiber. The effect of the dye bath pH can be attributed to the correlation between the dye structure and acrylic fibres. Acrylic fiber used in dyeing process has an anionic structure and dyed with cationic-dyes [10]. Acetic acid used in dyeing experiments performed seems to reduce the level of pH 4.5 at most. Initial pH level of dyestuff solution prepared without adding acid seems to be 5.5.

Retarder is a chemical substance in which dye molecules keep away from acrylic fiber. The dyeing rate is high at temperatures above the glass transition temperature due to a strong affinity between basic dyes and acrylic fiber, and the migration of basic dye molecules becomes very difficult after being adsorbed on the fiber. Therefore, a leveling agent is necessary in the dyeing bath for even color. Acrylic fibres vary significantly in the number of anionic sites available for sorption of cations, but level dyeing accrues when the number of cations in the system (retarder as well as dyes) is just enough to saturate the anionic sites in the fibre. This means that more retarder will be needed for fibres of high saturation value and for paler shades. Minimum and maximum retarder level was selected as 0.15 ml and 0.25 ml, respectively. Retarder level used in the factory under normal conditions is applied as 0.20 ml.

A liquid or gas added to a mixture to promote dispersion or to maintain dispersed particles in suspension. As dispergator auxiliary chemical affects the mixture ratio in solution of dyestuff, it is defined as a parameter in the study. The amount of dispergator affected the color of dyestuff directly and levels pertaining to parameter are determined related with the amount of dispergator. Minimum and maximum levels of dispergator were selected as 0.15 ml and 0.25 ml, respectively. Dispergator level used in Factory under normal conditions is applied as 0.20 ml. Fiber dyeing in process is performed under existing conditions are given in Table II.

TABLE II

EXISTING CONDITIONS IN DYEING PROCESS

Factors	Levels	Production Values
A	1	100 °C
B	-1	20 minute
C	-1	A
D	-1	A
E	0	5 gram
F	-1	4.5
G	0	0.2 ml
H	0	0.2 ml

III. TESTS PERFORMED TO DYED FIBERS AND SOLUTIONS

RSM output data were obtained by conducting tests of dyed fiber and solutions which remain in the bath after dyeing. Fiber after dyeing was made a measurement of color strength, fiber strength and color of the solution obtained after dyeing. These three outputs were transformed into one criterion as performance index with GRA.

A. The Indication of Dyed Fiber's Color Value

After conducting 82 experiments in orthogonal matrix defined with RSM, dyed fiber obtained was applied test for the indication of color value at Spectrophotometer machine. Spectrophotometer is an instrument that measures samples as color strengths (K/S) at multiple wavelengths from 400-700 nm, and their profiles of absorbance are compared to a standard. Measurement of samples taken from different areas of dyed fibers was conducted 10 times for performing color indication. The color strength of the dyed samples was evaluated by a light reflectance technique using the Perkin–Elmer, UV–vis Spectrophotometer. The relative color strength

(K/S values) was assessed using the following (1):

$$K/S = \frac{(1-R)^2}{2R} \tag{1}$$

where R = decimal fraction of the reflectance of the dyed fiber, K = absorption coefficient and S = scattering coefficient. The results obtained at the end of test are wanted to become closer to 33.43 as nominal value for minimizing difference of the color tone.

B. Color Indication of Solution after Dyeing

The result of dyeing application performed with basic dyeing stuffs of acrylic fibers, the color of solution in dyeing bath has given information about consistency of the amount of dye used in process. If the color of solution is darker than expected, it shows that the amount of unnecessary dyestuff is used during dyeing operation. For this reason, one of the target values in the study of optimization of dyeing process is to provide the minimization of solution color to reduce the amount of dyestuff in dye solution. After removing acrylic fiber from bath, samples taken from the remaining solution was subject to color test in the system which is used for solutions of spectrophotometer instrument. During measurement, color values having wavelength at 528 nm are taken into consideration. If color value is out of limit during the color definition performed by spectrophotometer instrument, solutions were proportionally diluted with pure water; results were multiplied with dilution proportion.

C. Strength Definition of Dyed Fiber

Dyed acrylic fiber in factory where the study was made is sent to yarn process which is the next stage. Fibers are intensely exposed to tensile strength in the yarn process. In this stage, protecting the resistance to tensile strength of acrylic fiber provides performance and productivity improving of yarn process. 10 tests made for every sample were obtained strength values at the moment of breaking.

IV. ANALYTICAL HIERARCHICAL PROCESS (AHP) FOR WEIGHT DETERMINATION

The designer of AHP which is a multi-criteria decision-making approach that can be used to solve complex problems is Saaty. Many researchers have been still showing interest to AHP which uses a multi-level hierarchical structure of objectives, criteria, sub criteria, and alternatives. The goal of AHP is integrating different measures into a single overall score for ranking decision alternatives. The main characteristic of AHP depends on pair-wise comparison judgments [11].

There are two different approaches that can be adopted for group decision making in AHP: The Aggregation of Individual Judgments (AIJ) and The Aggregation of Individual Priorities (AIP) [12]. AIJ method is used as the group becomes a new 'individual' and behaves like one; they are working together as team member. As for AIP, The group is assumed as separate individuals and either an arithmetic or geometric mean can be used to aggregate the individuals' priorities. In this study, we used AIP approach by applying geometric mean. The description is developed in three steps [13].

Step 1: Compose a pair-wise comparison decision matrix (A)

$$A = [a_{im}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \quad i,m = 1,2,\ldots,n. \tag{2}$$

Let a_1, a_2, ..., a_n denote the set of elements, while a_{im} represents a quantified judgment on a pair of elements, C_i and C_m. Saaty constitutes a measurement scale for pair-wise comparison. Hence, verbal judgments can be expressed by degree of preference: Equally preferred with 1, moderately preferred with 3, strongly preferred with 5, very strongly preferred with 7 and extremely preferred with 9; 2, 4, 6 and 8 are used for compromise between the above values. AHP matrices were constructed by three department managers in charge of dyeing process, production planning and quality. Geometric mean for group decision making were employed in combining matrices.

Step 2: Normalize the decision matrix. Each set of column values is summed. Then, each value is divided by its respective column total value. Finally, the average of rows is calculated and the weights of the decision-maker's objectives are obtained. A set of n numerical weights w_1, w_2, ..., w_i were obtained (see Table III and IV).

TABLE III
NORMALIZED AHP MATRIX

	Color value of fabric	Strength of fabric	Color of Dying Solution
Color value of fabric	0.464097	0.460372	0.486988
Strength of fabric	0.464097	0.460372	0.437666
Color value of dying solution	0.071805	0.079256	0.075347

Step 3: Do consistency analysis.

$$A.w_i = \lambda_{\max}.w_i \quad i=1, 2, \ldots, n. \tag{3}$$

Then consistency index (CI) is calculated as:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{4}$$

The consistency index of a randomly generated reciprocal matrix shall be called to the random index (RI), with reciprocals forced. The last ratio that has to be calculated is

CR (consistency ratio). Generally, if CR is less than 0.1, the judgments are consistent, so the derived weights can be used. The formulation of CR is:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{5}$$

For normalized matrix, CR = 0.008419 was obtained. As CR is less than 0.1, all judgments in Step 1 were accepted as consistent.

TABLE IV
WEIGHTS OF RESPONSES

	Color value of fabric	Strength of fabric	Color of dying solution
Weights	0.4705	0.4540	0.0755

V. GREY RELATIONAL ANALYSIS

Grey Relational Analysis is a quantitative methodology that depends on the level of similarity and variability among all factors used to measure the correlation degree of factors. Because of incomplete, poor, unclear information about system factors, relationships and structures, grey system theory was proposed as a useful tool by Deng [14]. The more similarities increase, the more factors correlate. GRA is used to evaluate and solve complicated interrelationships among multiple performance characteristics which can be converted into single grey relational grade which has a range generated between zero and unity. If the grey relational grade increases, the multiple performance characteristics are getting better and better. However, quality characteristic weights need still to be known, so that optimal process parameter setting combinations can be determined more accurately. Quality characteristics weights have played an important role in measuring the overall system performance. Dyeing process conditions are affected to reach an optimum and robust model as these weights change. In this study, we used GRA because of insufficient data. We made 82 experiments to reach the optimal parameter setting by using RSM. Otherwise, we must perform full factorial design of 3^8 (6561) for exact solution. But, this situation is time and money consuming. On the other hand, we will not be able to reach interval solution. RSM orthogonal matrix with 82 experiments is constructed by taking into consideration each parameter in three levels. In order to be able to combine three quality characteristics into one performance index, we used GRA method. GRA methodology is described as follows;

Step 1: Generate the referential series of $x_0 = (x_0(1), x_0(2), \ldots, x_0(j), \ldots, x_0(n))$, in which x_i is the compared series of $(x_i(1), x_i(2), \ldots, x_i(j), \ldots, x_i(n))$, where $i = 1,2,\ldots,m$. The compared series x_i can be represented in a matrix form

Step 2: Normalize data set. The series data can be treated using one of following three types: “larger is better”, “smaller is better”, “nominal is the best” [15].

Step 3: Calculate the distance of $\Delta_{0i}(j)$ -that is, the absolute value of difference between x_0 and x_i at the point $o_i(j)$.

Step 4: Calculate the grey relational coefficient $\gamma_{0i}(j)$ using (6):

$$\gamma_{0i}(j) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{0i}(j) + \zeta\Delta\max} \tag{6}$$

where $\Delta\min = \min_i \min_j \Delta_{0i}(j), \Delta\max = \max_i \max_j \Delta_{0i}(j)$ (7)

, and ξ is the distinguished coefficient ($\xi \in [0,1]$).

Step 5: Calculate the degree of the grey equation coefficient Γ_{0i}. If the weights (W_i) of criteria are determined, the grey relational grade is defined as follows (8):

$$\Gamma_{0i} = \sum_{j=1}^{n} [w_i(j) \;\; x \;\; \gamma_{0i}(j)] \tag{8}$$

According to GRA, if any of the alternatives has a higher grey relational grade than others, it is the most important (or optimal) alternative.

VI. OPTIMIZATION

A. GRA-RSM for Exact Level

For the 82 experiments run, the total mean of the grey relational grade was calculated and listed in Table V. It was ranked in order to understand the most significant parameter in the dyeing process. As a result, optimal parametric combination has been determined [15]. The optimal factor setting became $A_1B_0C_0D_0E_0F_0G_0H_0$ where number indicates level of factors (See Table VI).

TABLE V
RANK ORDER OF PARAMETERS WITH EXACT LEVELS

	Level -1	**Level 0**	**Level 1**	**max-min**	**rank**
A	0,44066	0,62594	0,69579	0,25512	1
B	0,56418	0,61403	0,57804	0,04985	4
C	0,57076	0,61456	0,57120	0,04380	8
D	0,56116	0,61741	0,57942	0,05626	2
E	0,56757	0,61291	0,57520	0,04534	7
F	0,56757	0,61291	0,57520	0,04534	6
G	0,57566	0,61943	0,56394	0,05550	3
H	0,57240	0,61605	0,56885	0,04721	5

While process was running under the optimal set with exact level, real manufacturing result of performance index was found as 0.660763 and performance index was predicted as 0.668502 by model.

TABLE VI
OPTIMAL SETTING OF GRA-RSM WITH EXACT LEVEL

Factors	Levels	Optimal Process Conditions
A	1	100 ˚C
B	0	30minute
C	0	B
D	0	B
E	0	5 gram
F	0	5
G	0	0,20 ml
H	0	0,20 ml

*Predicted value= 0,668502

B. RSM-GRA with Desirability for Interval Value

Box and Wilson [16] first introduced the concept of RSM as an important tool in modern quality engineering. The main aim of RSM is to obtain the optimum response. If there is more than one response then compromise optimum that does not optimize only one response should be considered. The objective at multi-response optimization is to determine process variables for optimizing several responses simultaneously. The selection of optimal parameter levels is a general problem in product-process design. A second-order polynomial model is widely employed to find an empirical relationship [17].
Generally, response surface first order model is (9):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \qquad (9)$$

β_0 and β_i are constant and x_i is independent variable [18]. First order models can be used for two level designs but they fail when additional interaction or effects are included. This way, a second order model is needed (10). It is:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{1 \le i \le j}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad (10)$$

β_{ij} belongs to coefficient of interaction parameters [19]. While determining of minimum, maximum and saddle points, a quadratic polynomial function is needed (11):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{1 \le i \le j}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad (11)$$

β_{ii} represents coefficient of quadratic parameters [20]. While searching for optimum conditions, the method of steepest ascent procedure is employed in the direction of the maximum increase in the response. When a system has multiple responses to given experimental factors, RSM often becomes unsatisfactory to solve this kind of problems, because what is optimal for one response may not be optimal for other responses [20]. There are several extensions for RSM to find the best compromise among multiple responses. One of the most popular methodologies is the desirability function approach [21]. The scale of the desirability function ranges between d=0, which suggests that the response is completely unacceptable, and d=1, which suggests that the response is exactly the target value. The value of d increases as the “desirability” of the corresponding response increases. The effect of independent variables on dependent variable can be found by using desirability function.

All experiment analysis was performed “response surface optimization” in DOE module of STATISTICA Software package. RSM model, while looking main effects of independent variables, considers two way interactions simultaneously. According to the option of “Linear Quadratic main effect + 2 way interactions”, model was formed. We searched for main effects and two-way interactions with this option. Equation (12) defines the individual desirability formulas.

$$d = \begin{cases} 0, & y \le y_{min} \\ (y\text{-}y_{min})/(y_{max}\text{-}y_{min}) & y_{min} \le y \le y_{max} \\ 1, & y \ge y_{max} \end{cases} \qquad (12)$$

y_{min} and y_{max} are the highest and lowest experimental values of y (response variable). In our study, the value found for minimum response variable (performance index) is 0.419128 and maximum response variable is 0.747016. Individual desirability function is defined as follows (13):

$$d = \begin{cases} 0, & y \le 0.419 \\ 0 \le y \le 1 & 0.419 \le y \le 0.747 \\ 1, & y \ge 0.747 \end{cases} \qquad (13)$$

Desirability levels for multi response RSM were defined (see Table VII). According to desirability level determined, interval values were found for independent variables (see Table VIII).

TABLE VII
DESIRABILITY LEVELS FOR MULTI RESPONSE RSM

Desirability Levels	Values for performance index
0	0.19
0.5	0.5987
1	1

A, E and A^2 factors based on ANOVA are important for % 95 confidence level. Optimal process conditions under this desirability level were found (see Table VIII) and a prediction is made for optimum conditions. The prediction result of performance index is 0.7422 and real manufacturing value of performance index is 0.6860.

TABLE VIII

OPTIMAL PARAMETERS FOR INTERVAL VALUES RSM

Factors	Levels	Production Values
A	0.72921	97.2921˚C
B	0.99868	39.9868 minute
C	-1	A
D	-1	A
E	0.27672	5.55344 gr
F	0.99992	5.49996
G	-0.0181	0.199095 ml
H	-0.068	0.1966 ml

Depending on RSM, meta model can be written as:

$$Y=0.622424 + 0.128A - 0.081A^2 + 0.007B + 0.0146B^2 + 0.0002C + 0.010C^2 - 0.0003D + 0.027D^2 + 0.009E-0.013E^2 + 0.004F + 0.023F^2 - 0.006G - 0.029G^2 - 0.002H - 0.002H^2 - 0.002AB - 0.002AC +0.0004AD + 0.007AE - 0.004AF - 0.001AG - 0.003AH + 0.006BC + 0.004BD + 0.008BE - 0.004BF - 0.001BG + 0.003BH + 0.002CD + 0.003CE + 0.001CF + 0.001CG + 0.002CH + 0.002DE + 0.001DF - 0.001DG + 0.004DH -0.005EF + 0.003EG + 0.003EH + 0.003FG + 0.006FH - 0.005GH \tag{14}$$

C. Artificial Neural Network (ANN)

Multi Layer Perceptron (MLP) is a feed forward neural network with one or more layers between input and output layer. Feed forward means that data flows in one direction from input to output layer (forward). This type of network is trained with the back propagation learning algorithm. MLPs are widely used for pattern classification, recognition, prediction and approximation. Multi Layer Perceptron can solve problems which are not linearly separable. In this study, orthogonal matrix based on RSM was used as input and performance index was selected as output of ANN. By using trail-error approach with 500 different kinds of networks were trained. MLP data was separated as 80 % train-20 % test. Then the best 10 networks were retained. According to the minimum testing error, MLP 8-7-1 having the best test value among 10 networks as given in Table IX. These networks were constructed from 3 layers with 8 inputs, one hidden layer with seven neurons and one output in the output layer. We want to compare parameters which are significant for the ANN system. There are several ways including Sensitivity Analysis, Fuzzy Curves, Perturb and Garson's algorithm to find significant parameters for ANN applications [22, 23 and 24].

TABLE IX

DIFFERENT NETWORK STRUCTURES

Net. Name	Training error	Test error	Hidden activation	Output activation
MLP 8-5-1	0.000126	0.000281	Exponential	Logistic
MLP 8-5-1	0.000151	0.000400	Exponential	Logistic
MLP 8-8-1	0.000019	0.000309	Tanh	Logistic
MLP 8-5-1	0.000131	0.000357	Tanh	Identity
MLP 8-7-1	0.000043	0.000417	Tanh	Identity
MLP 8-10-1	0.000365	0.000517	Tanh	Exponential
MLP 8-12-1	0.001068	0.000629	Gaussian	Identity
MLP 8-7-1	*0.000088*	*0.000240*	*Tanh*	*Exponential*
MLP 8-5-1	0.000046	0.000542	Tanh	Logistic
MLP 8-7-1	0.000292	0.000507	Tanh	Exponential

Relative importance of variables in ANN can be obtained by using GS. If each of its input variables is changed, sensitivity analysis can test the neural network predictions and, therefore whether the error rates would increase or decrease can be shown. Each variable in turn replaced with its mean value calculated from the training sample, and the resulting network error is recorded. The error will increase a great deal when an important variable changed; the error will not increase very much when an unimportant variable is removed [25]. Importance of input parameters is shown in Table X.

Since neural network algorithms use random number generators for fixing the initial value of the weights (starting points) of the neural networks, which often result in obtaining slightly different (local minima) solutions each time you run the analysis. Changing the seed for the random number generator used to create the train and test samples can change your results. Because of this reason, software was run ten times for optimal process conditions that were found by other methodologies. The mean GRA results were obtained and given in Table XI based on ANN model.

TABLE X

GLOBAL SENSITIVITY ANALYZE FOR GRA-RSM MODEL

Factors	Global Sensitivity
A	107.72
E	6.05
H	5.2
B	5.18
F	4.85
D	3.48
C	3.23
G	2.36

Optimal processing condition which was derived from GRA- RSM with interval level gives better results than GRA-RSM with exact level. All conditions which are constructed by chancing the levels of important parameters slightly were predicted by selected MLP- ANN model. Optimal conditions are given in Table XII for GRA-ANN model.

TABLE XI
10 REPEATED RUN FOR CONDITIONS OF EXACT AND INTERVAL LEVEL

Run	Case1[a]	Case 2[b]
(1-10) Mean	0.7026	0.7088

a represents GRA-RSM with exact level
b represents GRA-RSM with interval level

The manufacturing value of performance index under the optimal conditions of GRA-ANN model is 0.680532 and model prediction is 0.727032. When all three models were compared between each other based on performance index, the best one among all three models belongs to GRA-ANN depending on MSE and R^2 values. Minimum MSE and maximum R^2 values are the selecting criteria for GRA-ANN model. All modeling results are summed up in Table XIII.

VII. CONCLUSION

In this study, the performance of GRA-RSM and GRA-ANN model in the optimization of dyeing process conditions for carpet manufacturing was compared. GRA-ANN methodology showed superiority over GRA-RSM as a modeling technique in terms of the MSE and R^2.

TABLE XII
OPTIMUM PROCESS CONDITIONS FOR GRA-ANN MODEL

Factor Names	Levels	Production values
A	1	100 °C
B	0.99868	39.98 minute
C	-1	A
D	-1	A
E	0.55	6.1 gram
F	0.99992	5.49
G	-0.0181	0.199 ml
H	-0.068	0.1966 ml

As given in Table XIII, the best condition belongs to GRA-ANN model with interval level which has 0.727 GRA value. In the future study, there can be done two important things to improve the process conditions by determining quality characteristic weights as objective and comparing the other efficient modeling techniques which can be obtained good results, especially with Taguchi-GRA methodology.

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TABLE XIII
COMPARISON OF DIFFERENT METHODOLOGIES

Method Name	Predicted GRA	Manufacturing Values	Important Factors	MSE	R^2
Case 1*	0.6685	0.6607	A,D,G	0.00112	0.965
Case 2*	0.7423	0.6860	A,E and A^2	0.00112	0.965
Case 3*	0,7270	0.6805	A,E	0.00024	0.970
Case 4*	0.5387	0.5387			

Case 1: GRA-RSM with exact level, Case 2: GRA-RSM with interval level,
Case 3: GRA-RSM-ANN, Case 4: Existing Conditions.

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