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# Robust Parameter Design in Optimization of Textile Systems Using Response Surface and Dual Response Surface Methodologies

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**Abstract:** In this study, The preparation and production of multilamellar liposomes from Soya lecithin with 75% phosphatidylcholine were carried out and the behavior of liposomes in dye-bath at different temperature, time, Sodium Sulphate, pH and concentration (five factors) were considered and compared by two different optimization approaches, namely, with and without Robust Parameter Design (RPD) using standard design matrix of Response Surface Methodology (RSM) in both cases to produce representative data. The results of optimization methods for the data of recent published research article which was only based on general mean function show that the estimation of optimal factor values through new methodology of RPD approach is 86 percent more efficient.

**Key words:** Liposomes · Wool dyeing · Color strength (K/S) · Central composite design · Robust parameter design

## INTRODUCTION

Low temperature of wool dyeing has benefits such as lower energy conservation and wool fibers protection by either decreasing the temperature or shortening the processing time at high temperature during dyeing. The wool fabric dye at low temperature has both more natural feeling and improved durability, using some of the known synthetic auxiliaries in dye-bath during low-temperature dyeing [1]. Liposomes are spherical synthetic layers of phospholipids, which has been formed like closed vesicles with an aqueous core and ranging from 10 nm to 10 lm in diameter [2, 3]. Liposomes compose of lipid vesicle bilayers enclosing a volume. These structures have hydrophobic and hydrophilic parts. The hydrophilic part is composed of phosphate and choline groups, and the hydrophobic part is made up of hydrocarbon chain [4]. Phosphatidylcholine is the most widely used in biological lipid for producing liposomes. Wool dyeing and wool blends with liposomes have demonstrated to improve quality, energy conservation, and lower environmental impacts. Recently, commercial liposomes were incorporated into textile auxiliaries, mainly for wool dyeing [5-7]. This is a clean technology that has already been adapted by some textile industries. These are additional benefits for material-weight yield during subsequent spinning. These improved smoothness and mechanical properties of the dyed textiles, and showed a clear reduction in the contamination load of the dye-baths [8]. Use of liposomes as an auxiliary in wool dyeing can be related to the bilayer structure of lipids from the cell membrane complex (CMC) of wool that is similar to the liposomes and the action of this morphological fraction of the fiber in wool processing. A wool fiber includes of cuticle and cortical cells held together by the CMC and forms the continuous phase in the keratin [9]. This phase contains a small amount of lipid material. Diffusion properties of wool fibers are influenced by the lipid structure of the intercellular spaces that could act as ''solvents'' for hydrophobic chemical. The dyes diffuse with ease into swollen regions such as the CMC (intercellular diffusion) rather than through the cuticle cells (transcellular diffusion) [10]. Last few years, several articles have related the potential application of liposomes in wool dyeing. Meza *et al.* have investigated liposomes as doer in wool dyeing with acid [11, 12], disperse [13, 14] and metal complex dyes [15]. Also they have worked on the

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effects of commercially available liposomes as a simple additive [15]. Recently they used an optimized mixture of commercial liposomes and cationic surfactant to improve leveling property [17]. In the previous article, the influence of temperature on stability of multilamellar liposomes (MLV) in wool dyeing was studied, and it was found that the presence of 1% o.w.f. (on weight of fabric) of liposomes at 858C could improve the dye exhaustion of Irgalan Blue FBL on wool fabric. It has also reported that the wash fastness properties of dyed samples with liposomes have also improved. There is no report on using liposomes in wool dyeing with natural dyes. Therefore, we try to prepare and produce MLV from Soya lecithin with 75% phosphatidylcholine and study the influence of liposomes in dye-bath at different temperature, time, Sodium Sulphate, pH and concentration during wool dyeing with madder as a most famous natural dye. The dyeing temperature and time were optimized with optimum concentration of liposomes, and the morphology of the liposomes dyed samples has been investigated by scanning electron microscope (SEM).

The preparation and production of multilamellar liposomes from Soya lecithin with 75% phosphatidylcholine were carried out and the behavior of liposomes in dye-bath at different temperature, time, Sodium Sulphate, pH, and concentration were considered [18] and compared by two different optimization approaches, namely, with and without Robust Parameter Design [19]. Since it is impractical and unnecessary to produce all data points of the different combinations of levels of four considered factors, a standard design matrix, namely, Central Composite Design (CCD) of Response Surface Methodology (RSM) was used in both cases to produce representative data. This design of experiment, not only produces effective data, but also provides us an opportunity of modeling the whole experimental space.

## MATERIALS AND METHODS

The wool fabric with plain woven structure from 48/2 Nm yarns was supplied by Iran Merino. The fabric was scoured with 1% anionic detergent VEROLAN-NBO (supplied by Rodulf) at 708C for 45 min, and then washed with tap water, and dried at room temperature. Industrial grade of aluminium sulphate was used for mordanting of wool samples. Soya lecithin (containing 75% phosphatidylcholine) with phase transition temperature (Tc) of 2188C was gifted by Lipoid (Germany). Madder was prepared from Yazd providence of Iran. The reflectance spectra of the dyed samples were recorded on an ACS Spectra Sensor II integrated with an IBM-PC. The wash-fastness of the liposomes treated madder-dyed fabric were measured according to ISO 150-C01. For light-fastness measurements, the samples were exposed to the daylight for 7 days according to the daylight ISO 105-B01, and changes in the color (fading) were assessed by the blue scale. Also the dry and wet rub fastness of the samples evaluated according to ISO 105-X12. The sample pictures were taken with Philips XL30 SEM with 34000. The drop absorbency of the fabric samples was also measured by dropping of water droplet from 1 cm on the fabric surface on the glass by a small syringe. The time of complete absorption of the water droplets on the fabric surface was recorded and the mean value of 20 replicates was reported. Dyeing The mordanted wool samples were steeped in the dye bath with liquor-to-goods ratio of 40 : 1 that was prepared by 2% o.w.f. of extracted dye at pH 2-4 (acetic acid) with different concentrations of freshly prepared MLV liposomes (0, 1, 2, 3% o.w.f.). Dyeing was started at room temperature and then raised 28C/min to the final desired temperature including 75, 85, and 958C. The dyeing was carried out with liposomes and without liposomes in various times of 30, 45, and 60 min. The samples were rinsed with tap water and dried at room temperature. The amount of reflectance was selected at the maximum wavelength and the K/S value which is of the type "the larger the better" was calculated according to the Kubelka–Munk equation:

$$K/S = (1-R)^2/2R$$

**Methods:** Given the data from a crossed array, there are a number of potential approaches to directly modeling the mean and variance as a function of the control factors. A general approach is to assume that the underlying functional forms for the mean and variance models can be expressed parametrically. Assuming a $d$ point design with $n_i$ replicates at each location (i = 1, 2, … , $d$), the point estimators of the process mean and variance, $\bar{y}_i$ and $s_i^2$, respectively, form the data for the dual response system. Since the purpose of this article is to demonstrate the utility of a hybrid approach (combining a parametric and nonparametric approach to modeling) for robust design, we will consider an "off the shelf" model for the mean. An "off the shelf" model for the process mean is linear in the model parameters and can be written as:

Means model: $\bar{y}_i = x_i'\beta + g^{1/2}(x_i^{*\prime};\gamma)\varepsilon_i$ (1)

Where $x_i'$ and $x_i^{*\prime}$ are $1\times k$ and $1\times l$ vectors of means model and variance model regressors, respectively, expanded to model form, $\beta$ and $\gamma$ are $k\times 1$ and $m\times 1$ vectors of mean and variance model parameters, respectively, g is the underlying variance function, and $\varepsilon_i$ denotes the random error for the mean function. The $\varepsilon_i$ are assumed to be uncorrelated with mean zero and variance of one. Note that the model terms for the $i^{th}$ observation in the means model are denoted by $x_i'$ while the model terms for the variance model are denoted by $x_i^{*\prime}$. This allows for the fact that the process mean and variance may not depend on the same set of regressors.

Similar to the modeling of the mean, various modeling strategies have been utilized for estimating the underlying variance function. Bartlett and Kendall [12] demonstrated that if the errors are normal about the mean model and if the design points are replicated, the variance can be modeled via a log-linear model with the $d$ sample variances utilized for the responses. A great deal of work has also been done using generalized linear models for estimating the variance function. Although not an exhaustive list, the reader is referred to Box and Meyer [13], Aitkin [14], Grego [15], and Myers et al. [16-17]. As mentioned previously, since the purpose of this manuscript is to demonstrate the utility of a hybrid approach to modeling, we choose an "off the shelf" approach to variance modeling. The log-linear model proposed by Bartlett and Kendall [12] is a popular one [see Vining and Myers [18] and Myers and Montgomery [19] and is written explicitly as:

Variance model: $\ln(s_i^2) = g^*(X_i^*) + \eta_i = X_i^*\gamma + \eta_i$ (2)

Where $\eta_i$ denotes the model error term whose expectation is assumed to be zero and whose variance is assumed constant across the $d$ design points.

Assuming the model forms for the mean and variance given in (1) and (2), the model parameters are estimated using the following estimated weighted least squares (EWLS) algorithm:

**Step 1:** Fit the variance model, $\ln(s_i^2) = X_i^*\gamma + \eta_i$, via ordinary least squares (OLS), obtaining $\hat{\gamma}^{(OLS)} = (X^{*\prime}X^*)^{-1}X^{*\prime}y^*$ where $y^*$ is the $d \times 1$ vector of log transformed sample variances.

**Step 2:** Use $\hat{\sigma}_i^2 = \exp(X_i^{*\prime}\hat{\gamma}^{(OLS)})$ as the estimated variances to compute the $d\times d$ estimated variance–covariance matrix for the means model, $\hat{V} = diag(\hat{\sigma}_1^2, \hat{\sigma}_2^2, ..., \hat{\sigma}_d^2)$.

**Step 3:** Use $\hat{V}^{-1}$ as the estimated weight matrix to fit the means model, yielding $\hat{\beta}^{(EWLS)} = (X'\hat{V}^{-1}X)^{-1}X'\hat{V}^{-1}\bar{y}$ where $y^*$ denotes the $d \times 1$ vector of sample averages.

The algorithm above yields the following estimates of the process mean and variance functions:

Estimated process mean: $\hat{E}[y_i]^{(EWLS)} = x_i'\hat{\beta}^{(EWLS)}$, (3)

Estimated process variance: $\hat{Var}[y_i]^{(OLS)} = \exp(x_i^{*\prime}\hat{\gamma}^{(OLS)})$. (4)

Once estimates of the mean and variance have been calculated, the goal becomes finding the operating conditions for the control factors such that the mean is as close as possible to the target while maintaining minimum process variance.

Any control factor which influences the expression in (4) is known as a dispersion factor. Any control factor that does not influence the expression in (4) but does influence the expression in (3) is known as an adjustment factor. When both dispersion and adjustment factors are present, the robust design problem can be approached in a two-step fashion. Specifically, levels of the dispersion factors are chosen so as to minimize the estimated process variance in (4), and then the levels of the adjustment factors are chosen so as to bring the estimated process mean in (3) to a desired level. If only dispersion factors are present and these factors also influence the process mean, the researcher is left with finding the levels of the control factors that yield a desirable trade-off between low variance and a deviation from the targeted mean. This is often accomplished via minimization of an objective function such as the squared error loss (SEL):

$$SEL = E[y(x) - T]^2 = \{E[y(x)] - T\}^2 + Var[y(x)], \quad (5)$$

Where T denotes the target value for the process mean. Minimization can be accomplished via non-linear programming using a method such as the generalized reduce gradient or the Nelder–Mead simplex algorithm. The SEL approach is also useful when adjustment factors are present but are not strong enough to bring the mean to the targeted value. Note that the determined set of optimal operating conditions is highly dependent on quality estimation of both the mean and variance functions. Misspecification of the forms of either the mean or variance models can have serious implications in process optimization [20, 21].

Table 1: Statistical summary of variables and Observed Data

| | | | |
|---|---|---|---|
| **Study Type** | Response Surface | **Runs** | 26 |
| **Initial Design** | Central Composite | **Blocks** | No Blocks |
| **Design Model** | Quadratic | | |

| Factor | Name | Units | Type | Low Actual | High Actual | Low Coded | High Coded | Mean | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|
| A | Temp | C | Numeric | 75.00 | 89.00 | -1.000 | 1.000 | 82.269 | 5.758 |
| B | Time | min | Numeric | 37.00 | 54.00 | -1.000 | 1.000 | 45.827 | 6.992 |
| C | Concentration | mg/ml | Numeric | 1.70 | 3.40 | -1.000 | 1.000 | 2.583 | 0.699 |
| D | Sodium Sulphate | % | Numeric | 15.00 | 27.00 | -1.000 | 1.000 | 21.231 | 4.936 |
| E | pH | | Numeric | 2.50 | 3.60 | -1.000 | 1.000 | 3.071 | 0.452 |

Table 2: Design Matrix of the Experiment

| Std | Run | Block | Factor 1 A:Temp C | Factor 2 B:Time min | Factor 3 C:Concentratio mg/ml | Factor 4 D:Sodium Solpl % | Factor 5 E:pH | Response 1 K/S 1 | Response 2 K/S 2 | Response 3 K/S Bar |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Block 1 | 89.00 | 54.00 | 1.70 | 27.00 | 2.50 | 22.5 | 23.03 | 22.77 |
| 22 | 2 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 3.05 | 20.25 | 21.67 | 20.96 |
| 6 | 3 | Block 1 | 89.00 | 37.00 | 1.70 | 27.00 | 3.60 | 25.25 | 26.07 | 25.66 |
| 8 | 4 | Block 1 | 75.00 | 54.00 | 1.70 | 27.00 | 3.60 | 15.25 | 16.03 | 15.64 |
| 10 | 5 | Block 1 | 75.00 | 54.00 | 3.40 | 27.00 | 2.50 | 21.9 | 20.55 | 21.23 |
| 7 | 6 | Block 1 | 75.00 | 37.00 | 3.40 | 27.00 | 3.60 | 21.5 | 21.89 | 21.69 |
| 15 | 7 | Block 1 | 82.00 | 60.98 | 2.55 | 21.00 | 3.05 | 18.5 | 19.49 | 18.99 |
| 21 | 8 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 4.05 | 20.75 | 20.78 | 20.77 |
| 25 | 9 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 3.05 | 20.66 | 20.99 | 20.83 |
| 19 | 10 | Block 1 | 82.00 | 45.50 | 2.55 | 31.93 | 3.05 | 20.89 | 20.01 | 20.45 |
| 16 | 11 | Block 1 | 82.00 | 45.50 | 1.00 | 21.00 | 3.05 | 22.55 | 23.99 | 23.27 |
| 4 | 12 | Block 1 | 89.00 | 54.00 | 3.40 | 15.00 | 2.50 | 13.25 | 14.25 | 13.75 |
| 9 | 13 | Block 1 | 89.00 | 37.00 | 3.40 | 15.00 | 3.60 | 29.58 | 27.55 | 28.67 |
| 11 | 14 | Block 1 | 75.00 | 37.00 | 1.70 | 15.00 | 2.50 | 22.67 | 23.09 | 22.88 |
| 23 | 15 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 3.05 | 21.89 | 21.55 | 21.72 |
| 14 | 16 | Block 1 | 82.00 | 30.02 | 2.55 | 21.00 | 3.05 | 18.67 | 18.89 | 18.28 |
| 24 | 17 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 3.05 | 20.11 | 20.99 | 20.55 |
| 18 | 18 | Block 1 | 82.00 | 45.50 | 2.55 | 10.07 | 3.05 | 20.99 | 21.05 | 21.02 |
| 13 | 19 | Block 1 | 94.75 | 45.50 | 2.55 | 21.00 | 3.05 | 28.45 | 30.86 | 30.06 |
| 3 | 20 | Block 1 | 75.00 | 54.00 | 3.40 | 15.00 | 3.60 | 17.88 | 19.87 | 18.88 |
| 20 | 21 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 2.05 | 20.22 | 20.89 | 20.56 |
| 5 | 22 | Block 1 | 89.00 | 54.00 | 1.70 | 15.00 | 3.60 | 28.5 | 27.45 | 27.98 |
| 2 | 23 | Block 1 | 89.00 | 37.00 | 3.40 | 27.00 | 2.50 | 23.67 | 22.09 | 22.88 |
| 17 | 24 | Block 1 | 82.00 | 45.50 | 4.10 | 21.00 | 3.05 | 24.01 | 25.12 | 24.66 |
| 12 | 25 | Block 1 | 69.25 | 45.50 | 2.55 | 21.00 | 3.05 | 19.22 | 20.89 | 20.05 |
| 26 | 26 | Block 1 | 82.00 | 45.50 | 2.55 | 21.00 | 3.05 | 20.55 | 21.76 | 21.15 |

**Experimental Design:** The Central Composite Design used for experimental plan with five variables (liposomes amount, temperature, time, Sodium Sulphate, and pH ) along with their ranges and K/S amount measured (two repeated measures and their average) for each test of design matrix are shown in Table 1 and 2, respectively.

Table 3: Estimates of Regression Coefficients along with their Related Statistics

| Factor | Coefficient Estimate | df | Standard Error | 95% CI Low | 95% CI High | VIF |
|---|---|---|---|---|---|---|
| Intercept | 21.12 | 1 | 0.18 | 20.65 | 21.59 | |
| A-Temp | 2.75 | 1 | 0.17 | 2.31 | 3.19 | 2.65 |
| B-Time | -0.080 | 1 | 0.17 | -0.52 | 0.36 | 2.65 |
| C-Concentration | 0.38 | 1 | 0.17 | -0.058 | 0.82 | 2.65 |
| D-Sodium Solph | -0.16 | 1 | 0.17 | -0.60 | 0.28 | 2.65 |
| E-pH | 0.058 | 1 | 0.17 | -0.38 | 0.50 | 2.65 |
| AB | -1.42 | 1 | 0.25 | -2.07 | -0.77 | 3.59 |
| AC | -1.68 | 1 | 0.25 | -2.33 | -1.03 | 3.59 |
| AD | 0.36 | 1 | 0.25 | -0.29 | 1.01 | 3.59 |
| AE | 2.90 | 1 | 0.25 | 2.25 | 3.54 | 3.59 |
| BC | -1.71 | 1 | 0.25 | -2.36 | -1.07 | 3.59 |
| BD | 0.27 | 1 | 0.25 | -0.38 | 0.92 | 3.59 |
| BE | 0.77 | 1 | 0.25 | 0.12 | 1.42 | 3.59 |
| CD | 1.35 | 1 | 0.25 | 0.70 | 2.00 | 3.59 |
| CE | 2.00 | 1 | 0.25 | 1.35 | 2.64 | 3.59 |
| DE | 0.97 | 1 | 0.25 | 0.32 | 1.62 | 3.59 |
| $A^2$ | 1.15 | 1 | 0.097 | 0.91 | 1.40 | 1.02 |
| $B^2$ | -0.63 | 1 | 0.097 | -0.88 | -0.38 | 1.02 |
| $C^2$ | 0.83 | 1 | 0.097 | 0.58 | 1.07 | 1.02 |
| $D^2$ | -0.15 | 1 | 0.097 | -0.40 | 0.10 | 1.02 |
| $E^2$ | -0.17 | 1 | 0.097 | -0.42 | 0.079 | 1.02 |

Table 4: The Summary Statistics of fitted model

| | | | |
|---|---|---|---|
| Std. Dev. | 0.44 | R-Squared | 0.9970 |
| Mean | 21.78 | Adj R-Squared | 0.9849 |
| C.V. % | 2.02 | Pred R-Squared | 0.5391 |
| PRESS | 147.36 | Adeq Precision | 40.811 |

Also the influence of the variable on the results Y [color strength (K/S)] is adjusted using the following second order polynomial function:

$$\Upsilon = b_0 + \Sigma\, b_i\, X_i + \Sigma\, b_{ij}\, X_i\, X_j + \Sigma\, c_i\, X_i^2 \quad i \geq j$$

In this equation, b0 is an independent term according to the mean value of the experimental plan, bi are regression coefficients that explain the influence of the variables in their linear form, bij are regression coefficients of the interaction terms between variables, and ci are the coefficients of quadratic form of variables. Equation regression coefficients bi, bij, ci and the determination coefficient R2 are shown in Table 3 and 4.

Therefore, the final model is of the following form:

Final Equation in Terms of Coded Factors

| K/S Bar = | | |
|---|---|---|
| +21.12 | -1.68 * A * C | +2.00 * C * E |
| +2.75 * A | +0.36 * A * D | +0.97 * D * E |
| -0.080 * B | +2.90 * A * E | +1.15 * $A^2$ |
| +0.38 * C | -1.71 * B * C | -0.63 * $B^2$ |
| -0.16 * D | +0.27 * B * D | +0.83 * $C^2$ |
| +0.058 * E | +0.77 * B * E | -0.15 * $D^2$ |
| -1.42 * A | +1.35 * C * D | |

Table 5: Analysis of Variance for Surface Quadratic Model

Response 3 K/S Bar

ANOVA for Response Surface Quadratic Model

Analysis of variance table [Partial sum of squares - Type III]

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 318.74 | 20 | 15.94 | 82.32 | < 0.0001 | significant |
| *A-Temp* | *50.10* | *1* | *50.10* | *258.78* | *< 0.0001* | |
| *B-Time* | *0.042* | *1* | *0.042* | *0.22* | *0.6608* | |
| *C-Concentratio* | *0.97* | *1* | *0.97* | *4.99* | *0.0758* | |
| *D-Sodium Solpl* | *0.16* | *1* | *0.16* | *0.84* | *0.4017* | |
| *E-pH* | *0.022* | *1* | *0.022* | *0.11* | *0.7495* | |
| *AB* | *6.15* | *1* | *6.15* | *31.77* | *0.0024* | |
| *AC* | *8.62* | *1* | *8.62* | *44.55* | *0.0011* | |
| *AD* | *0.40* | *1* | *0.40* | *2.05* | *0.2112* | |
| *AE* | *25.64* | *1* | *25.64* | *132.45* | *< 0.0001* | |
| *BC* | *8.96* | *1* | *8.96* | *46.27* | *0.0010* | |
| *BD* | *0.22* | *1* | *0.22* | *1.16* | *0.3306* | |
| *BE* | *1.82* | *1* | *1.82* | *9.41* | *0.0279* | |
| *CD* | *5.57* | *1* | *5.57* | *28.76* | *0.0030* | |
| *CE* | *12.17* | *1* | *12.17* | *62.87* | *0.0005* | |
| *DE* | *2.88* | *1* | *2.88* | *14.89* | *0.0119* | |
| *$A^2$* | *27.60* | *1* | *27.60* | *142.58* | *< 0.0001* | |
| *$B^2$* | *8.25* | *1* | *8.25* | *42.60* | *0.0013* | |
| *$C^2$* | *14.12* | *1* | *14.12* | *72.94* | *0.0004* | |
| *$D^2$* | *0.46* | *1* | *0.46* | *2.36* | *0.1852* | |
| *$E^2$* | *0.60* | *1* | *0.60* | *3.08* | *0.1398* | |
| Residual | 0.97 | 5 | 0.19 | | | |
| *Lack of Fit* | *0.20* | *1* | *0.20* | *1.06* | *0.3612* | *not significant* |
| *Pure Error* | *0.77* | *4* | *0.19* | | | |
| Cor Total | 319.71 | 25 | | | | |

Table 6: Constraints ofModel

Constraints

| Name | Goal | Lower Limit | Upper Limit | Lower Weight | Upper Weight | Importance |
|---|---|---|---|---|---|---|
| Temp | is in range | 75 | 89 | 1 | 1 | 3 |
| Time | is in range | 37 | 54 | 1 | 1 | 3 |
| Concentration | is in range | 1.7 | 3.4 | 1 | 1 | 3 |
| Sodium Solphate | is in range | 15 | 27 | 1 | 1 | 3 |
| pH | is in range | 2.5 | 3.6 | 1 | 1 | 3 |
| K/S Bar | maximize | 13.75 | 30.06 | 1 | 1 | 3 |

Table 7: Optimal Solution for the Model

Solutions

| Number | Temp | Time | Concentration | Sodium Solpha | pH | K/S Bar | Desirability |
|---|---|---|---|---|---|---|---|
| 1 | 88.65 | 44.22 | 3.10 | 26.97 | 3.60 | 30.3282 | 1.000 |

Table 8: Optimal Factor Values with PRD Approach

| Temprature | Time | Concentration | Sodium Solphate | pH | K/S |
|---|---|---|---|---|---|
| 95 | 40 | 3.67 | 21 | 3.8 | 35 |

The ANOVA (Table 5) with concordance with the above results shows that not only model is significant but temperature, concentration, pH, and many of interaction and second order effects are also significant.

In this connection two of the surfaces are given in Figure 1 as an example.

The constraints of model are as table 6.

The optimal solution based upon the above constraints is as table 7.

A surface for the above solution is given in Figure 2.

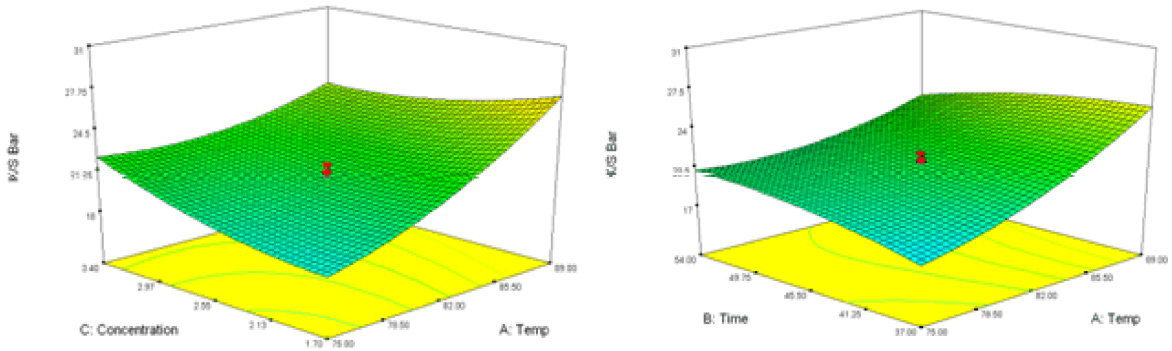


Fig. 1: Two of the surface for K/S

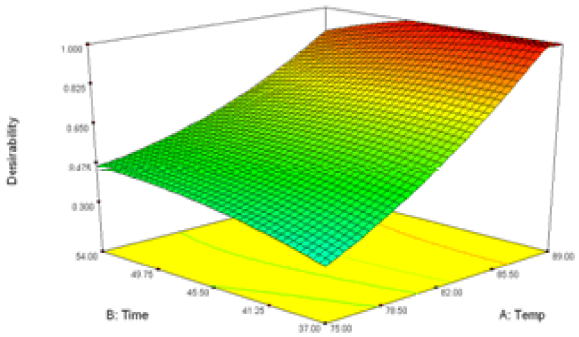


Fig. 2: A Surface for the Solution

However, the results of optimal solution for dual response surface which is referred to as parameter approach with MSE = 0.07 is summarized in table 8.

## CONCLUTION

The analysis results of using parametric model with RPD approach in which it uses functional mean along with a variance model show that the calculated mean square error (MSE) in this model (MSE = 0.07) is less than half of the MSE of parametric model without RPD approach (MSE = 0.19). Also, the obtained K/S amount which its maximization is desired is increased, tremendously.

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