

Doehlert 4-Variable Design for the Optimization of Lead Biosorption Using Activated Carbon Derived From Palm Kernel Cake

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ABSTRACT: The aim of the present investigation was to study the effects of four different process parameters such as initial lead concentration (10 to 30 mg L⁻¹), pH (3.5 to 6.5), dosage concentration (10 to 50 g L⁻¹) and temperature (20 °C to 40 °C) using activated carbon derived from Palm kernel cake as the adsorbent for the removal of hazardous lead metal from aqueous solution. Doehlert Design of Response Surface Methodology was employed to model the biosorption process by a second order quadratic model. Optimization of the response surface model predicted a 91.80% maximum removal of lead at the optimum process conditions of initial lead concentration: 21 mg L⁻¹, pH: 4.6, adsorbent dosage: 26 g L⁻¹ and temperature: 32 °C. The validation experiment carried out at the optimum process conditions confirmed the predicted values. The results demonstrated the potential use of activated carbon of palm kernel cake as a novel adsorbent for the optimal removal of lead using 4-variable Doehlert design.

KEYWORDS: Doehlert design; response surface methodology; biosorption, activated carbon; palm kernel cake.

I. INTRODUCTION

Public sensitivity to the presence of heavy metals in aquatic bodies is of great concern since they cannot be decayed or treated biologically. Further the unavailability of inexpensive technologies of waste water is an all time challenge to industrialists and environmentalists. Lead is discharged into natural waters from a wide range of industries such as storage batteries, tetra ethyl lead manufacturing, lead smelting, mining, plating, ammunition and the ceramic glass industries [1].

The permissible amount of lead in potable water is 0.05mgL⁻¹ [2]. Health disorders such as anemia, encephalopathy and hepatitis are caused due to the presence of excess lead in potable water. At times lead ions get immobilized for years and the metabolic disorders caused due to their presence cannot be identified [3]. Some commonly used techniques to eliminate heavy metal pollution include precipitation, ultra filtration, electrode deposition, cementation, ion-exchange, selected solvent extraction, activated carbon adsorption and biological processes. Adsorption is most often used for treatment of waste water containing heavy metals in view of its ease.

Among several chemical and physical methods, the adsorption onto activated carbon has been found to be superior to other techniques because of its capability for adsorbing a broad range of adsorbates efficiently and

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simplicity of design [4]. Activated carbon due to its high surface area, micro porous character and surface chemistry has been proven to be an effective adsorbent for the removal of heavy metals from industrial waste water [5]. Despite its frequent use in the water and waste industries, activated carbon remains an expensive material [6]. In view of the high cost of activated carbon, a lot of research has been directed to the development of low-cost activated carbon from cheap and readily available materials. Among the low-cost raw materials are the agro-forestry and agro-industrial residues. A wide variety of carbons have been prepared from agricultural wastes such as olive seeds, rice husks, walnut shells, palm shells, hazelnut shells, almond shells, pistachio nut shells and apricot stone [7-12]. Each of the carbons has characteristic properties and variation exists in the efficiency of removal of a range of heavy metal ions from solution. There is a constant need to investigate the potential of various raw materials as activated carbon precursors, depending on their costs and availability. Because of their wide usage in industry, the demand of the activated carbon is increasing year by year. Commercial activated carbon is quite expensive. As such, the industry now seeks for the cheaper activated carbon derived from agriculture waste or residues. The residues can be oil seed cakes, rice husk, sawdust or other carbonaceous material. The aim of the present research is to study the efficiency of activated carbon made from palm kernel cake (PKC) to optimally remove lead using 4-variable Doehlert experimental design.

After screening of the key parameters, the conventional technique for optimization is the “one factor at a time” method in which a single parameter is varied while fixing all others at a specific level. This method ignores the interaction among the process variables and might lead to unreliable results and conclusions, while requiring a large number of experiments. The disadvantage of single parameter optimization process can be eliminated by optimizing all the parameters collectively using statistically planned experimental design like Doehlert [13] which is based on the strategy of Response Surface Methodology (RSM). The optimization process based on RSM involves three major steps: 1) conducting the statistically designed experiment, 2) fitting the experimental data with quadratic model and determining the corresponding coefficients, and 3) predicting the response and checking the adequacy of the model. These techniques were used by many researchers for process optimization [14-16]. The present study reports the application of Doehlert experimental design to optimize the biosorption of lead using activated carbon obtained from Palm Kernel Cake (PKC) (*Elaeis guineensis*).

II. EXPERIMENTAL PROCEDURES

2.1. Preparation of Activated carbon

In this work activated carbon was prepared from PKC. The cake was collected from the local palm oil distillery unit of Vizianagaram district in Andhra Pradesh, India. The cake was washed, sundried and heated in the oven for 12 hours at 55 °C. The Carbonization process was accomplished in a muffle furnace. A known amount of PKC was introduced into the furnace which was heated to the desired temperatures of 800 K for 2hr. The charcoal was then soaked in a 25% concentrated solution of CaCl₂, the gases that are formed due to exothermic reaction are allowed to escape for the first 3 min. and then covered with a lid for 24 hours. The sample is shifted to a drain tray where it is allowed to drain for 30 minutes and repeated washed with distilled water to remove traces of chemical. The washed sample is now placed in an oven for 2 hours at 110°C. The chemically activated carbon of PKC is then cooled and sealed in polythene bags to keep away from moisture and dust for further use.

2.2 Preparation of metal solution

Analytical reagent (AR) grade of chemicals were used for analysis. Appropriate amount of Pb (NO₃)₂ salts were dissolved in distilled water to prepare a stock solution of lead. The test solutions of lead ions were prepared by appropriate dilution of stock solution. The concentrations of lead ions varied between 10 and 200 mgL⁻¹. Before adding the adsorbent, the pH of each test solution was adjusted to the required value with 0.1 M NaOH or 0.1 M HCl.

2.3 Doehlert experimental design of response surface methodology (RSM)

This article is regarding the optimization of four variables using Doehlert design and supposedly the first of its kind. The strategy of any experimental design consists of carrying out a limited number of planned experiments that involve interaction of process variables and to model the obtained data by the relation:

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$$y \text{ (response)} = f(\mathbf{x}, \boldsymbol{\beta}) \text{ (model)} + \boldsymbol{\varepsilon} \text{ (error)} \tag{Eq.1}$$

The surface represented by $f(\mathbf{x}, \boldsymbol{\beta})$ is called a response surface. The response can be represented graphically, either in the three-dimensional space or as two-dimensional contour plots that help visualize the shape of the response surface. In RSM, a quadratic model is used to relate the vector of scaled independent variables (\mathbf{x}), with the data of dependent variable (\mathbf{y}). The unknown coefficients ($\boldsymbol{\beta}$) are estimated by multiple regression. For the case of 4-variable process, the response is given by the equation:

$$\mathbf{y} = \beta_0 + \beta_1 \mathbf{x}_1 + \beta_2 \mathbf{x}_2 + \beta_3 \mathbf{x}_3 + \beta_4 \mathbf{x}_4 + \beta_{12} \mathbf{x}_1 \mathbf{x}_2 + \beta_{13} \mathbf{x}_1 \mathbf{x}_3 + \beta_{14} \mathbf{x}_1 \mathbf{x}_4 + \beta_{23} \mathbf{x}_2 \mathbf{x}_3 + \beta_{24} \mathbf{x}_2 \mathbf{x}_4 + \beta_{34} \mathbf{x}_3 \mathbf{x}_4 + \beta_{11} \mathbf{x}_1^2 + \beta_{22} \mathbf{x}_2^2 + \beta_{33} \mathbf{x}_3^2 + \beta_{44} \mathbf{x}_4^2 + \boldsymbol{\varepsilon} \tag{Eq.2}$$

where, \mathbf{y} is the measured response, and $\boldsymbol{\varepsilon}$ is the random experimental that is assumed to follow normal probability distribution with constant experimental variance. The random error is estimated in the form of residual which is the difference between the observed and predicted values of \mathbf{y} . The square terms, ($\mathbf{x}_1^2, \mathbf{x}_2^2, \mathbf{x}_3^2, \mathbf{x}_4^2$), account for the curvature of the response. The maximum response will be obtained when all the four coefficients ($\beta_{11}, \beta_{22}, \beta_{33}, \beta_{44}$) are negative. They are all positive for the case of a minimum surface. The optimum value (stationary point) will be found by solving the derivatives of Eq.2 with respect to the four independent variables after equating them with zero values.

$$\delta y / \delta x_1 = \delta y / \delta x_2 = \delta y / \delta x_3 = \delta y / \delta x_4 = 0 \tag{Eq.3}$$

The solution at this point, i.e., $x_{1s}, x_{2s}, x_{3s}, x_{4s}$, is called stationary point. This stationary point might represent any one of the following situations which also depends on sign of the Eigen values of matrix, \mathbf{B} , as mentioned in Table 1:

Table 1: Eigen Values vs. Nature of response surface

Eigen values	Nature of Response Surface
All positive	Minimum
All negative	Maximum
Mixed Signs (some positive and some negative)	Saddle surface, where optimum is not identified
Zeroes	Flat surface

1. A point of maximum response.
2. A point of minimum response.
3. A saddle point.

Writing the second order model (Eq.2) in matrix notation, we have

$$\mathbf{y} = \beta_0 + \mathbf{x}' \boldsymbol{\beta} + \mathbf{x}' \mathbf{B} \mathbf{x} \tag{Eq.4}$$

Where, $\mathbf{x} = [x_1 \ x_2 \ x_3 \ x_4]'$; $\boldsymbol{\beta} = [\beta_{12} \ \beta_{13} \ \beta_{14} \ \beta_{23} \ \beta_{24} \ \beta_{34}]$; and the matrix \mathbf{B} is given by

$$\mathbf{B} = \begin{pmatrix} \beta_{11} & \beta_{12}/2 & \beta_{13}/2 & \beta_{14}/2 \\ \beta_{21}/2 & \beta_{22} & \beta_{23}/2 & \beta_{24}/2 \\ \beta_{31}/2 & \beta_{32}/2 & \beta_{33} & \beta_{34}/2 \\ \beta_{41}/2 & \beta_{42}/2 & \beta_{43}/2 & \beta_{44} \end{pmatrix} \tag{Eq. 5}$$

The matrix \mathbf{B} is a (4 × 4) symmetric matrix whose main diagonal elements are the pure quadratic coefficients (β_{ij}), rest being the halves of interaction coefficients. The derivative of \mathbf{y} w.r.t. elements of vector \mathbf{x} when equated to $\mathbf{0}$ is given by

$$\delta y / \delta \mathbf{x} = \boldsymbol{\beta} + 2 \mathbf{B} \mathbf{x} = \mathbf{0} \tag{Eq.6}$$

The stationary point is the solution to the above equation, or

$$\mathbf{x}_s = (-1/2) \mathbf{B}^{-1} \boldsymbol{\beta} \tag{Eq.7}$$

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Furthermore, by substituting the above equation (7) in equation (4) we can find the predicted response at stationary point as:

$$y_s = \beta_0 + 0.5 \sum x_s \beta \tag{Eq.8}$$

The percentage removal of metal by biosorption is represented as the response (dependent variable) and given by the relation:

$$y = 100(C_o - C_f) / C_o \tag{Eq.9}$$

where, C_o is the initial concentration, C_f is the final concentration.

The natural variables, X_i , are associated with the scaled variables, x_i , by the relation

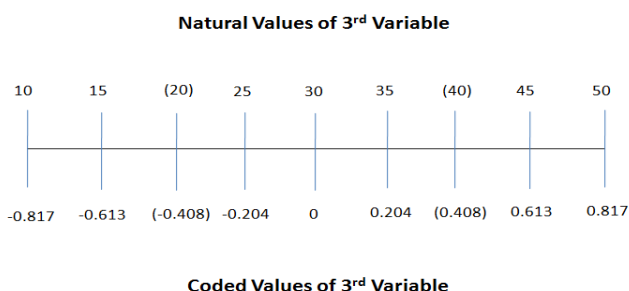
$$X_i = X_{mid,i} + (X_{max,i} - X_{mid,i}) * x_i / X_{max,i} \tag{Eq.10}$$

Where, the middle and maximum values for scaled and natural variables are listed in Table 2.

Table 2: Experimental range and levels of the variables

Variables	Range and Levels						
Coded Variable1 (x_1)	-1	-0.5	0	0.5	1		
Initial metal concn. (X_1)	10	15	20	25	30		
Coded Variable2 (x_2)	-0.866	-0.577	-0.289	0	0.289	0.577	0.866
pH (X_2)	3.5	4.0	4.5	5.0	5.5	6.0	6.5
Coded Variable3 (x_3)	-0.817	-0.613	-0.204	0	0.204	0.613	0.817
Dosage (X_3)	10	15	25	30	35	45	50
Coded Variable4 (x_4)	-0.791	0	0.791				
Temperature (X_4)	20	30	40				

It is to be noted that the levels for the third variable are not uniformly distributed in the specified range. The coded values and corresponding natural values are doubled between 2nd and 3rd levels and similarly between 5th and 6th levels as shown below. Hence the values mentioned within the brackets are not included in the design as far as 3rd variable is concerned.



Doehlert design presents a number of benefits over the other designs of Response Surface Methodology. Firstly, the design demands few experiments; secondly, the number of levels is dissimilar to the number of variables. Depending on their relative importance a large number of levels can be assigned to the selected variable. To obtain maximum information of the system, seven levels are assigned to the variable which exhibit strong effect. Thirdly, Doehlert design is more efficient than Central Composite design or Box-Behnken design (Ferreira et al., 2004) [17] in terms of lesser number of runs. The 4-variable Doehlert design with 26-runs is shown in Table 3.

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Table 3: Doehlert 4-variable experimental design along with experimental and predicted values

Expt No.	Coded Values				Natural Values				% biosorption of Lead	
	x ₁	x ₂	x ₃	x ₄	X ₁	X ₂	X ₃	X ₄	Experimental	Predicted
1	0	0	0	0	20	5.0	30	30	91.45	91.37
2	0	0	0	0	20	5.0	30	30	91.04	91.37
3	0	0	0	0	20	5.0	30	30	91.57	91.37
4	0	0	0	0	20	5.0	30	30	91.02	91.37
5	0	0	0	0	20	5.0	30	30	91.26	91.37
6	0	0	0	0	20	5.0	30	30	91.89	91.37
7	1	0	0	0	30	5.0	30	30	85.43	85.61
8	0.5	0.866	0	0	25	6.5	30	30	86.08	86.59
9	0.5	0.289	0.817	0	25	5.5	50	30	85.38	84.45
10	0.5	0.289	0.204	0.791	25	5.5	35	40	84.82	84.75
11	-1	0	0	0	10	5.0	30	30	82.34	82.78
12	-0.5	-0.866	0	0	15	3.5	30	30	88.12	88.23
13	-0.5	-0.289	-0.817	0	15	4.5	10	30	87.68	84.91
14	-0.5	-0.289	-0.204	-0.791	15	4.5	25	20	84.78	84.85
15	0.5	-0.866	0	0	25	3.5	30	30	89.24	88.89
16	0.5	-0.289	-0.817	0	25	4.5	10	30	87.86	87.80
17	0.5	-0.289	-0.204	-0.791	25	4.5	25	20	84.57	84.49
18	-0.5	0.866	0	0	15	6.5	30	30	85.31	84.42
19	0	0.577	-0.817	0	20	6.0	10	30	88.38	88.42
20	0	0.577	-0.204	-0.791	20	6.0	25	20	86.38	86.41
21	-0.5	0.289	0.817	0	15	5.5	50	30	80.62	82.53
22	0	-0.577	0.817	0	20	4.0	50	30	85.81	87.62
23	0	0	0.613	-0.791	20	5.0	45	20	86.36	86.33
24	-0.5	0.289	0.204	0.791	15	5.5	35	40	81.48	81.56
25	0	-0.577	0.204	0.791	20	4.0	35	40	87.98	87.95
26	0	0	-0.613	0.791	20	5.0	15	40	88.63	88.66

III. RESULTS AND DISCUSSIONS

3.1 Optimization of biosorption using Doehlert Design

The selection of the range for process variables is extremely important when planning the experimental design; otherwise, after completion of the experimental runs, the optimal conditions, obtained by response surface methodology, might not be found within the experimental region. From the results of preliminary experimental runs, the four variables (initial lead concentration, pH, biosorbent dosage and temperature) were identified as the potential variables for the percentage biosorption of lead. Out of them, pH and biosorbent dosage showed stronger effect on percentage biosorption of lead, and hence they were assigned seven levels, followed by initial lead concentration which was assigned five levels and temperature was assigned three levels. A summary of the independent variables and their range and levels is presented in Table 2.

Twenty six experimental runs (Table 3) including three replicates at the center point were carried out for 60 minutes of contact time. By using the 'regstats' MATLAB program, Eq.2 was fitted with the observed data of Table 3 and the resulting model with the estimated coefficients is given by the following equation.

$$y = 91.3715 - 1.4162 x_1 - 1.7635 x_2 - 1.7303 x_3 + 0.1296 x_4 + 0.8666 x_1 x_2 - 0.3127 x_1 x_3 + 1.8467 x_1 x_4 - 2.3391 x_2 x_3 - 2.7818 x_2 x_4 - 3.7064 x_3 x_4 - 7.1782 x_1^2 - 3.3913 x_2^2 - 4.9808 x_3^2 - 6.0766 x_4^2 \quad \text{Eq. (11)}$$

The predicted percentage biosorption of lead that resulted from Eq. (11) is in close agreement with the experimental values as evident from the last column of Table 3, and hence the above equation was deemed to be adequate in representing the percentage biosorption of lead under the specified range of experiments. Application of Eq.7 with the

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estimated coefficients yielded the optimal settings for coded variables as x_1 : 0.097146, x_2 = -0.24553, x_3 = -0.16172, x_4 = 0.13094 that predicted a maximum 91.80% removal of lead. In terms of natural variables, they are found to be:

$$\text{Initial lead concentration} = 21 \text{ mg L}^{-1}$$

$$\text{pH} = 4.6$$

$$\text{Biosorbent dosage} = 26 \text{ g L}^{-1}$$

$$\text{Temperature} = 32^\circ\text{C}$$

$$\% \text{ maximum biosorption of Lead by PKC} = 91.80\%$$

When a validation experiment was carried out at the values of optimum process variables, a 92.96 % biosorption of lead was observed which is very close to the maximum predicted by Eq.11. Moreover, the observed value is well within the 95% intervals as shown in Table 4.

Table 4: Model coefficients estimated by multiple linear regression

Term	Coefficient	Estimated value	p-value
Constant	β_0	91.3715	0.0000
Initial lead concentration	β_1	1.4162	0.0401
pH	β_2	-1.7635	0.0112
Biosorbent dosage	β_3	-1.7303	0.0185
Temperature	β_4	0.1296	0.8224
Initial lead concentration*pH	β_{12}	0.8666	0.5529
Initial lead concentration*dosage	β_{13}	0.3127	0.8695
Initial lead concentration*Temperature	β_{14}	1.8467	0.3066
pH * dosage	β_{23}	-2.3391	0.1981
pH * Temperature	β_{24}	-2.7818	0.1303
Dosage*Temperature	β_{34}	-3.7064	0.0537

The Confidence interval explains how much variation could be possible with a certain model. The uncertainty in the specific estimate is reflected by prediction interval, and logically the error is greater than the confidence interval. Unlike confidence interval, prediction interval predicts the spread for ‘individual’ observation, rather than the mean value.

Eigen values of the matrix **B** (from Eq.5) are found to be: -8.7254; -6.6625; -3.5552, -2.6838. As all the Eigen values are negative, the response surface for biosorption of lead represents a unique maximum.

The significance of each coefficient in Eq. (11) was determined by student’s t-test and p-values, which are listed in Table 5. Usually, the coefficients with p-values < 0.05 are included in the fitted equation. A model is said to be hierarchical if the presence of higher-order terms (such as interaction and second-order terms) requires the inclusion of all lower-order terms contained within those of higher order. Many regression model builders believe that hierarchy is a reasonable model building practice when fitting polynomials. So in this model all the terms are included using the hierarchical principal, even though values of ‘p’ for certain coefficients are high. However, the deletion of such terms would not affect the optimality of Eq.11.

Table 5 ANOVA for the entire quadratic model

Source of variation	Sum of squares (SS)	Degree of freedom (d.f.)	Mean squares (MS)	F-value	Probe>F
Model	229.7473	14.0000	16.4105	10.3212	0.0002
Error	17.4897	11.0000	1.5900		
Total	247.2370	25.0000			

$$R=0.998688; R^2 =0.997379; \text{Adjusted } R^2 =0.992661$$

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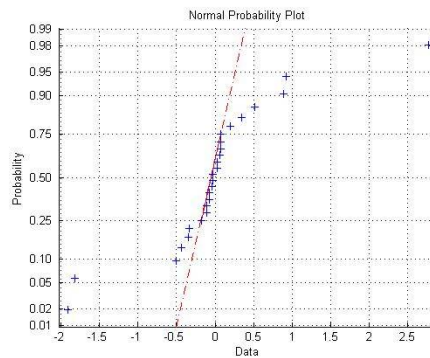
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$P_{model} > F = 0.0002$

3.2 Normal Probability Plot:

A normal probability plot (Fig.1) is a useful graph for assessing whether data relating to Eq.11 comes from a Normal distribution. Regression of RSM model makes the assumption that the underlying distribution of the data is Normal. The plot provides some assurance that the assumption of Normality is not being violated, and may provide an early warning of a problem with the assumptions. If all the data points fall near the line, the assumption of Normality is reasonable. But, if the data is non Normal, the plus signs may follow a curve. As the points in Fig.3 lie on the line, it is presumed that the observed response data points of Table 3 follow Normal distribution.

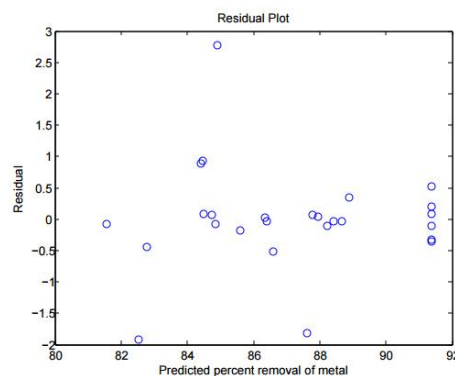
Fig.1 Normal probability plot



3.3 Residual Plot:

Residuals are estimates of experimental error obtained by subtracting the observed responses from the predicted responses. Examination of residuals is a key part of all statistical modeling. Careful observation of residuals would give the information whether the assumptions made for Eqs.1&2 are reasonable and the choice of model is appropriate. Residuals can be thought of as elements of variation unexplained by the fitted model. It is evident from the Fig. 2 that the residuals are scattered randomly above and below the zero line without any significant trend. Hence it is assumed that the residues are randomly distributed with a constant variance.

Fig.2 Residual plot



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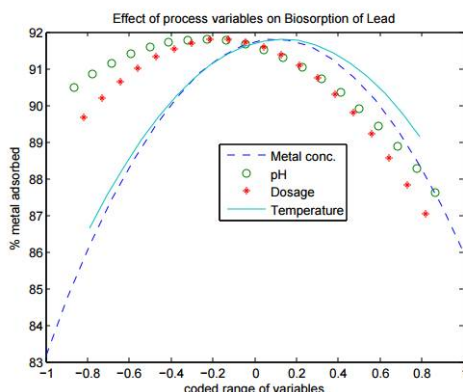
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3.4 Perturbation Plot:

This plot depicts the result of individual parameters on the percentage removal of Lead. The plot does not show any interaction effects among the parameters, but it is similar to the behavior of a process where experiment is carried out by varying one parameter at a time. The plot assists in comparing the result of all the parameters at an exact point in the design space. The outcome is estimated from Eq.11 by changing a particular scaled variable in its entire range while keeping the others at their optimum levels. The curve for a variable indicates that the response is sensitive even to a small change in particular variable in the specified range; whereas a straight line indicates that the particular variable is not critical in affecting the process. The perturbation plot (Fig.3) is a useful aid in visualizing the effect of each variable graphically. From the figure it is evident that each of the process variables has its individual effect on the biosorption process. However, pH had more pronounced effect on metal removal. Keeping the levels of initial metal concentration and dosage of PKC at a fixed value, a change in pH would drastically affect the metal uptake. The curves of other two variables almost coincide in the entire range and hence their influence is equally appreciable in affecting the metal uptake.

Fig.3 Perturbation plot of lead removal at the optimal conditions of pH, lead concentration, biosorbent dosage and temperature



The goodness of fit of the response surface model can be examined by the determination coefficient (R^2). The model predicts the response efficiently when the R^2 value is closer to 1. The value of the determination coefficient ($R^2=0.92926$) indicates that 92.92% of the variability in the response could be explained by the model. Three dimensional response surface plots (Figs.4A to 4F) were drawn from Eq.11 to visualize the impact of any two variables (while the others are kept at their optimum) on the response using MATLAB-7 software. Fig. 4A shows the interaction effect of initial lead concentration and pH on percentage biosorption of lead. It is evident that the percentage biosorption of lead increased and reached the maximum in the range of 10-21 mg L⁻¹ initial lead concentration, but slowly decreased beyond this concentration. Similarly, pH in the range from 4 to 6 had shown significant effect on lead biosorption.

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Fig.4A. Response surface and contour plot of Initial lead concentration vs. pH on percentage biosorption of lead

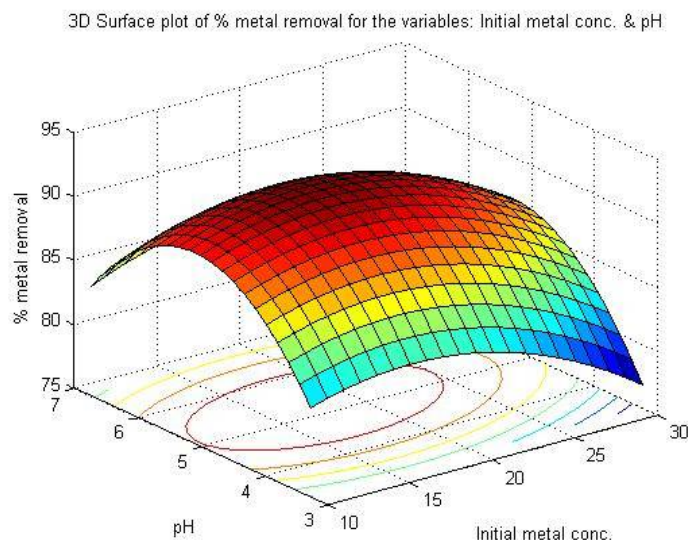


Fig.4B depicts the effects of initial metal concentration and biosorbent dosage on the percentage biosorption of lead. It is observed that the increase of biosorbent dosage from 20 to 45 g L⁻¹, metal concentration (in the range 12 to 24) influenced the biosorption of lead

Fig. 4B. Response surface and contour plot of Adsorbent dosage vs. Initial lead concentration on percentage biosorption of lead

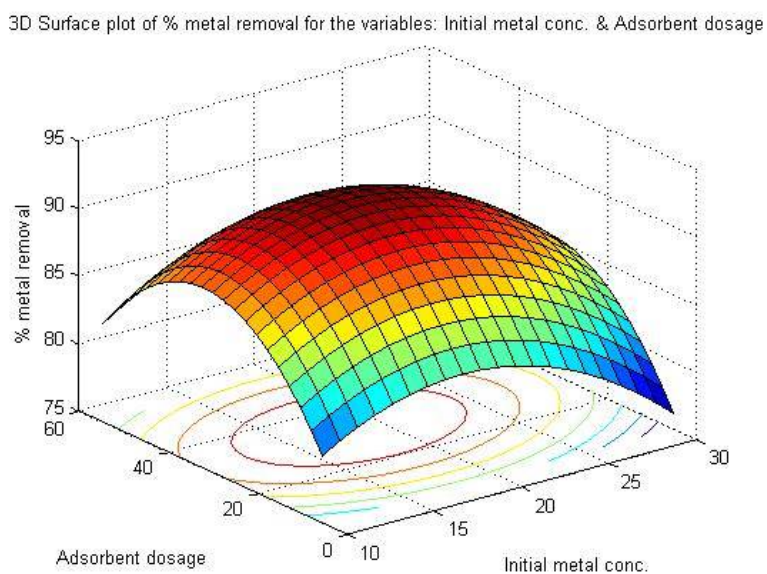


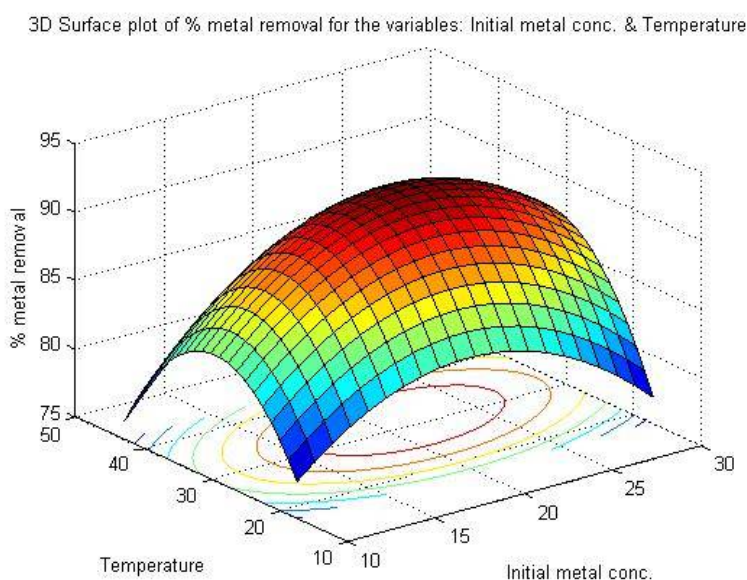
Fig. 4C represents the outcome of the interaction between initial lead concentration (in the range 14 to 26) and temperature (in the range 25 to 38) on lead biosorption at the optimum pH and dosage

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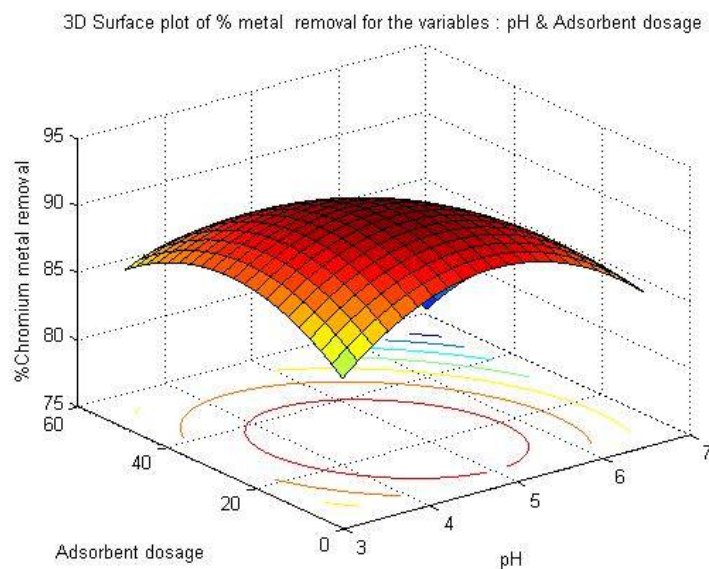
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Fig. 4C. Response surface and contour plot of Initial lead concentration vs. Temperature on percentage biosorption of lead.



The interaction affect of pH (in the range 2 to 6) and adsorbent dosage (in the range 2 to 42) can be seen in Fig. 4D

Fig. 4D. Response surface and contour plot of Adsorbent dosage vs. pH on percentage biosorption of lead



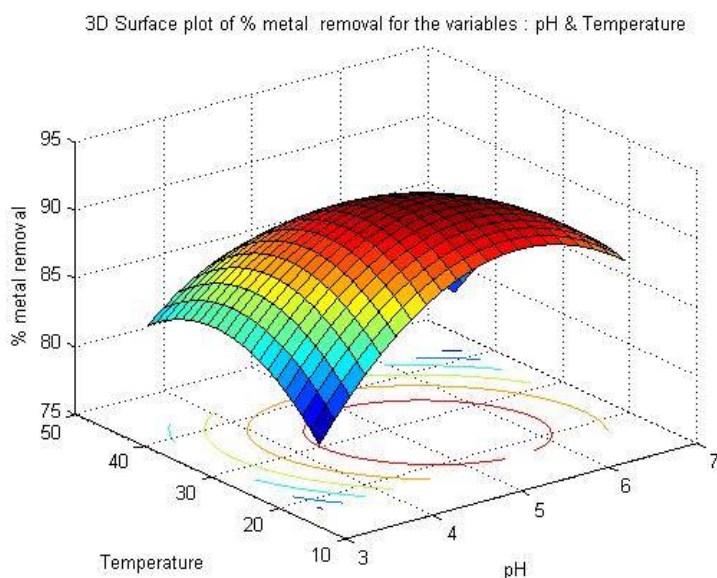
Surface and contour plots showing the interaction effect between pH (in the range of 4 to 6) and temperature (in the range 15 to 35) are portrayed in Fig.4E

Fig. 4E. Response surface and contour plot of Temperature vs. pH on percentage biosorption of lead

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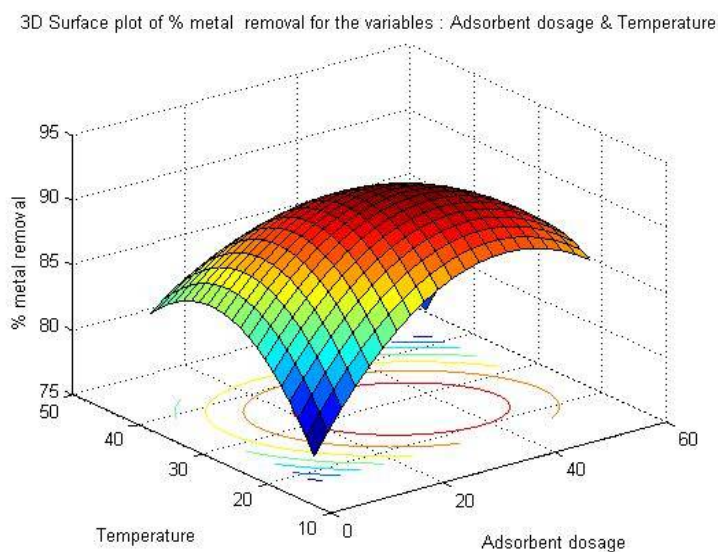
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The effect of temperature in the range of 20 to 35, and adsorbent dosage in the range of 20 to 45 on biosorption is depicted in Fig 4F

Fig.4F. Response surface and contour plot of Temperature vs. Adsorbent dosage on percentage biosorption of lead



IV. CONCLUSION

Experiments were performed at different levels of initial metal concentration, pH, adsorbent dosage and temperature for the removal of lead using Doehlert 4-variable design. The results of present investigation showed that

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activated carbon derived from Palm Kernel Cake was an efficient biosorbent for lead ion in dilute solutions. Maximum removal of lead (91.8%) was observed at the initial metal concentration: 21 mg L^{-1} , pH: 4.6, adsorbent dosage: 26 g L^{-1} and temperature : 32°C . When a validation experiment was carried out at the optimum process conditions, the observed maximum percentage removal of lead was found to be closer to that of the predicted maximum. The results confirmed the utility of activated carbon derived from PKC as a potential adsorbent for the effective removal of lead from aqueous solution using Doehlert 4-variable design involving a minimum experimental effort of 26 runs.

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