Optimization Of Adsorption Of Congo Red By Corn Cob Powder Using Support Vector Machine

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Abstract Escalating environmental information is compelling waste initiators to bear in mind new alternatives like adsorption for the removal of dye in tinted waste water. Owing to outstanding expenses of commercially activated carbon (CAC), inexpensive adsorbent with high adsorption capacity have achieved growing consideration. The current study offers with exploitation of an inexpensive, waste adsorbent material of corn cob powder and enhancing the situations for removing the Congo red dye from an aqueous solution with the help of central composite design (CCD) experiment. UV-Visible Spectrophotometer is applied to establish the concentration of dye within the waste water. The surface uptake capability (SUC) of corn cob powder will increase when the initial concentration of dye, contact time and temperature becomes increased. The SUC decreases with increase in measure of adsorbent and pH level of the medium. Support Vector Machine (SVM) employing central composite design turned into used at the required mixtures of five self determining factors (dye attention, adsorbent dosage, contact time, pH and temperature). By using these subsequent circumstances, dye concentration 80 mg/L, adsorbent dosage 0.05 g/L, contact time 15 min, pH 7.0 and temperature 300C, we have achieved the maximum level of adsorption capacity as 50.0 mg/g. This research procedure will take long time to analyze and it is prolonged manner. But growing pollutants will motive severe harm to the environment. So it's miles vital to pick out on fastest answer for this problem. In this proposed approach a Support Vector Machine based online solution is achieved for eliminating the Congo red dye from the aqueous solution. The SVM expected SUC is as compared with an experimental result. The accuracy of the proposed SVM Model has been predicted by the simulation result. The study specifies the corn cob powder becomes efficient and also an inexpensive opportunity for removing the Congo red dye.

Keywords Adsorption, optimization, Congo red, corn cob, surface vector machine

1. Introduction

Significant situations established inside the fabric dyeing sewages are recognized to obstruct the traditional organic sewage control techniques. Exclusion of dye from the sewages is therefore a chief
trouble forcing factory to keep in mind novel alternatives for the sewage remedy and discarding [3]. Among all wastewater management, adsorption marketing has been found to be an effective way to remove industrial dyes from industrial waste. [7]. The adsorption capability of the activated carbon is meritorious for natural contaminants but its excessive price and failure to restore cause reduction in its business utility [8]. Thus, inexpensive adsorbents with excessive adsorption capabilities inclusive of waste material, natural materials derived from agriculture, microbial adsorbents have brought interest [9, 10]. A fundamental benefit of adsorption is that it is utilized in situ and incorporated through lots of structures inside the maximum ecological behavior [11]. Thus, in this study, a design named multi-variant investigational design based on arithmetical technique which consists of Response Surface Methodology (RSM) and Artificial Neural Network (ANN) method carried out and turned technique modeling [12,13]. In recent times, ANN methods are getting used in lots of Science and Engineering areas to clear up ecological Engineering troubles inclusive of metal elimination [14] and fabric dye removal [15,16]. Artificial Neural Networks are taken into consideration as an assuring device since their easiness towards replication, much fewer time needed for model improvement than the conventional numerical models [17], precise calculation potential with few numbers of experiments and identity for optimum working situations for the plant worker [18].

A regression model is of air fine with the aid of the use of the SVM technique in Spain city place at neighborhood scale has been advanced [19]. To attain the goal, a quite nonlinear model of the air first-rate has been created by using the experimental statistics from the year 2006–2008 in the Aviles city nucleus based on SVM strategies. The chemical method issues a fault diagnosis which contains a non-stop stirred tank reactor and a warmness exchanger and is assessed through SVM technique [20]. The effects are in comparison with ANN outcomes. The SVM technique [21] has been developed by the CHEMPROT song at BioCreative VI entry. This machine is examined based on the three devices namely support vector device, convolution neural network, and a persistent neural network. The combined output can be blended the usage of bulk choosing or loading for very last calculations. The development and evaluation of systems able to extracting association among chemicals/drug and genes/proteins from biomedical literature. It participates with systems: (a) an SVM gadget which has a rich set of capabilities has been extracted from the parse graph and (b) a band of neural networks that makes use of LSTM networks and generate capabilities along the shortest path of dependencies [22]. It additionally combines the predictions from the 2 systems with the purpose of increasing performance.

Though ANN gives higher result, for non-linear software like elimination of Dye from water it is not appropriate. It does no longer provide accurate answer for the non-linear trouble. In this manuscript, the Support Vector Machine (SVM) was made to determine the extend of dye in the water. SVM is a structured learning algorithm used for model reputation issues brought on by Boser, Guyon and Vapnik. It is used for each pattern recognition and pattern mapping trouble. In this paper SVM used for mapping of different parameters with SUC level.

2. Experimental

Materials

*Preparation of dye solution:*

Congolese red (CR) dye was made in 1883 by Paul Bottiger. It is indicated as sodium salt of benzidinediazo - bis - 1 - naphthylamine - 4 - sulfonic acid (Formula: C_{32}H_{22}N_{6}Na_{2}O_{6}S_{2}; molecular weight: 696.66 g / mol). \( \lambda_{\text{max}} = 497 \) nm. Congo red was basic dye selected for the present investigation. The chemicals used were made of Analar grade and also used without further purifications. The stock solution (1000 mg/litre) of Congo red dye (MW = 319.85 g/mol; Manufacture = Ran Baxy) were prepared by diluting 1 gram of dye with doubly distilled water in 1000 ml standard measuring flask to get a dye solution 1000 ppm.

*Preparation of the adsorbent:*
A corncob is the significant center of a maize ear. The ear of the corncob plant is also taken into anxiety a "cob" or "pole" but it is not totally a "pole" till the ear is eliminated from the plant cloth approximately the ear. Each line of corn on a corncob has the equal variety of seeds. Advantages of the corncob powder had been excessive adsorption potential for dyes, cheap, do not require any luxurious pre-remedy, green and without problems available in huge quantities.

Corn cobs discover use inside the following programs:
- Industrial furnish of the chemical furfural
- Fiber in fodder for ruminant farm animals

The corn cobs were amassed from agricultural restraint and have been washed repeatedly with distilled water thereby it removes dust and different insoluble impurities. After that the corn cobs are cut to a small size and made to dehydrate in the shade and then in the air oven for 333K for several hours until they explode. Then the dehydrated corn cobs were crushed in a chopper to acquire corncob powder. The powder changed into surpassed thru a 2 hundred mesh (100mm) sieve, and become protected in a hygienic air tight glass bottle for the use as adsorbent.

**Buffer solution:**
The acidic and basic buffer solutions were prepared using the acetic acid, aqueous ammonia, ammonium chloride and sodium acetate. The buffer solutions were made to maintain the pH values of the solutions carry the range of 3.0, 5.0, 7.0, 8.0, 9.0 and 10.0.

**Batch Adsorption Studies:**
In these adsorption studies various tests were performed using the batch adsorption process under five test conditions to identify the consequences of fluctuations in process parameters.
- a) Initial concentration of Congo red
- b) Contact time (min)
- c) Dose of the adsorbent (corn cob Powder)
- d) Initial pH of the dye solution
- e) Temperature

The Batch Adsorption experiment was taken out in 250 ml narrow mouth bottle. A mixture was made by mixing a well-known amount of corn cop powder with 50 ml of a wet dye solution, had a certain concentration. NM bottles are stored in the stem, at constant temperature for a known time period at a constant velocity (800 rpm). Parameters such as adsorbent volume, contact time and adsorption temperature were controlled. After the adsorption release is complete, the mixture is immediately centered on a laboratory centrifuge (REMI centrifuge). The adsorbent remains fast and the remaining dye concentration is determined spectrophotometrically. Percentage removal of CR dye is calculated by the following formula

\[
\% \text{ Removal} = (C_i - C_e)/C_i \times 100 \quad \text{---(1)}
\]

The maximum CR adsorbed (mg / g) mass calculated based on the weight balance as given below

\[
q \text{ or SUC} = (C_i - C_e)V/m \quad \text{---(2)}
\]

where,
- q is adsorption capability in mg/g
- C_i is initial dye conc.in mg/L
- C_e is final dye conc.in mg/L
- V is vol. of final solution in ml
- m is quantity of adsorbent in gram
- SUC is Surface uptake capacity

3. **Support Vector Machine**
Support Vector Machine (SVM) is one of the categories of discrimination officially defined by the hyper-extractive plane. In other words, you are provided with labeled data (supervised reading); the algorithm provides the best hyper flight output set in new models. In two separate areas, a hyper plane is a line that separates the plane into two parts where each class lay in each other surface. The purpose...
of the support vector machine algorithm is to locate a hyper plane in an N-dimensional gap (N—the number of features) that particularly organizes the data points. We look at the data points of the form \\
\{(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4) \ldots \ldots., (x_n, y_n)\}.

SVM separators are derived from a group of hyper aircraft, \((wx) + b = 0\) \(w \in \mathbb{R}^N, b \in \mathbb{R}\), corresponding to optional functions \(f(x) = \text{sign}((wx) + b)\). We can reveal that the best hyper plane, shown as one that contains a large margin of separation between the two given categories. Logical usage, the user shows the kernel function; the change here \(\varphi(.)\) is not explicitly stated. Given the function of kernel \(K(x_i, x_j)\), the mutation \(\varphi(.)\) Is calculated by its Eigen functions (concept in performance analysis). Eigen's works are complex to make clear. This is why we are showing the kernel function without any modification. There exists another view that, kernel function is being an inner product, is really a similar measure between the objects. Some of the kernel functions are Linear, Quadratic, Polynomial and Radial Basis Function (RBF). The most common kernel function used here is Gaussian RBF kernel, which is given by \\
\[ K(x, y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}} \quad (3) \]

where \(\sigma^2\) is the variance of the Gaussian kernel.

The two user-defined parameters appear to be important in building an SVM network. One is the sigma \((\sigma^2)\) parameter and the other is the cost of gamma function \((C)\).

Development of SVM for SUC:
The input Data set for SVM has five independent significant factors (adsorbent dosage, contact time, pH, dye concentration and temperature) at five levels (-2, -1, 0, +1, +2) and output is SUC.

The algorithm for obtaining SUC values using the SVM Network is given below.
a. Set the input, output, training and testing data values of the SVM network.
b. Perform both training and test output levels using the Min max method.
c. The training process is done with standard data set by the appropriate planning parameters.
d. After the training process, the test will continue. The difference between the calculated output and the required output is checked.
e. The normal value of this difference is taken as MSE value.

This gamma and sigma values are selected by trial and error method to reach the minimum MSE values.

4. Results And Discussions
The high concentration removal of Congolese red dye was turned and obtained with a minimum pH (32.75 mg / g), while the upper pH only surprisingly SUC involvement decreased to 3.75 mg / g. The pH level solution determines the external adsorbent charge, ionization level and adsorbent speciation, which has an effect on dye advertising. In conclusion, ionic dyes release colored ions into the solution [23]. As the pH ratio level decreases, additional protons are found here to indicate the amino groups of corn cob powder molecules and thus form well-charged groups of \(\text{NH}_3\) groups. This will increase the demand for energy between the anionic group \((-\text{SO}_3^2-)\) of the dye and the proposed amino group \((-\text{NH}_3)\) of cork, which causes an increase in dye production [9].

Effect of the dye concentration:::
The CR dye concentration has been varied from 20 to 100 ppm for the same amount of adsorbent dosage 0.1g and contact time. Early concentration versus percentage exclusion of CR was plotted (Fig. 1). The result shows that advertising adsorption increases with a decrease in the previous concentration of CR dye and this was due to the oversupply of the adsorption sites on the exterior of
the corncob powder. The higher receive of CR at low concentration may be pointed to the accessibility of more dynamic sites on the exterior of the corncob powder for smaller number of CR species. The curve of CR adsorption are single, smooth and continuous to suggest the availability of a single monolayer of CR dye containing molecules other than corncob powder.

**Fig.1:** Effect of dye concentration on the removal of CR dye by CCP

*Effect of the mass of adsorbent:*

The process of changing the amount of adsorbent filtration of CR dye (30 ppm) has an effect and it is shown in Fig. 2. It was monitored that if the adsorbent dose raises, then the elimination percentage of CR dye from the sedimentary solution will increase. It is clear that by increasing the amount of the adsorbent, the number of sorption places accessible for sorbent – dye ion communication is increased, thus ensuing in the enlarged percentage elimination of CR from solution in every cases.

**Figure 2:** Effect of dose of adsorbent on the removal of CR dye by CCP

*Effect of agitation time:*

The capture of CR from the aqueous solution by agricultural waste adsorbents increases while the campaigning time was changed from 5 to 60 minutes and reaches equilibrium in 60 minutes at 30°C. The high in adsorption of Congo red with increase in campaigning time may be accredited to the increased intra particle dispersion occurring at long shaking time. The data gained are graphically represented in Fig. 3.
Effect of pH:

The consequence of pH level for the adsorption of dye was approved at different pH values such as 3, 4, 5, 7, 8, 9 and 10. The pH of the medium versus percentage removal of CR was plotted. The outcome pointed out that at low pH the elimination of dye was highest and at high pH the dye removal was little (Fig. 4).

Optimization of important variables by CCD:

CCD has been used on the particular combination of five self-governing important factors (pH, dye concentration, dose of the adsorbent and agitation speed) at five levels (-2,-1, 0, +1, +2) to study the connections among them and thereby to conclude their best levels (Table 1).

| Factor | Variable | Range and level |
|--------|----------|----------------|
| X1     | [dye] ppm | -2  30  50  80  100 |
| X2     | Dose (g)  | 0.05  0.075  0.1  0.15  0.25 |
| X3     | CT        | 10  15  20  30  60 |
| X4     | pH        | 3  5  7  8  10 |
| X5     | Temp      | 30  40  45  50  60 |
Table 1. Experimental ranges and levels of the independent process variables in the CCD

The plan template for the variables tested in 85 test values compared with the investigational results and the results obtained as the hypothetically forecasted responses (using the equation model) is shown in Table 2.

| Run No. | X₁ | X₂ | X₃ | X₄ | X₅ | SUC (mg/g) |
|---------|----|----|----|----|----|------------|
|         |    |    |    |    |    |            |
| 1       | -2 | 0  | -1 | -2 | -2 | 9.70       |
| 2       | -1 | 0  | -1 | -2 | -2 | 13.50      |
| 3       | 0  | 0  | -1 | -2 | -2 | 20.50      |
| 4       | 1  | 0  | -1 | -2 | -2 | 25.90      |
| 5       | 2  | 0  | -1 | -2 | -2 | 32.75      |
| 6       | -2 | 0  | -1 | -1 | -2 | 9.20       |
| 7       | -1 | 0  | -1 | -1 | -2 | 13.05      |
| 8       | 0  | 0  | -1 | -1 | -2 | 21.40      |
| 9       | 1  | 0  | -1 | -1 | -2 | 25.45      |
| 10      | 2  | 0  | -1 | -1 | -2 | 28.60      |
| 11      | -2 | 0  | -2 | 0  | -2 | 8.50       |
| 12      | -1 | 0  | -2 | 0  | -2 | 12.40      |
| 13      | 0  | 0  | -2 | 0  | -2 | 18.35      |
| 14      | 1  | 0  | -2 | 0  | -2 | 23.40      |
| 15      | 2  | 0  | -2 | 0  | -2 | 23.80      |
| 16      | -2 | -2 | -1 | 0  | -2 | 18.20      |
| 17      | -1 | -2 | -1 | 0  | -2 | 24.90      |
| 18      | 0  | -2 | -1 | 0  | -2 | 37.50      |
| 19      | 1  | -2 | -1 | 0  | -2 | 50.00      |
| 20      | 2  | -2 | -1 | 0  | -2 | 43.90      |
| 21      | -2 | -1 | -1 | 0  | -2 | 11.27      |
| 22      | -1 | -1 | -1 | 0  | -2 | 16.87      |
| 23      | 0  | -1 | -1 | 0  | -2 | 27.87      |
| 24      | 1  | -1 | -1 | 0  | -2 | 36.87      |
| 25      | 2  | -1 | -1 | 0  | -2 | 40.67      |
| 26      | -2 | 0  | -1 | 0  | -2 | 9.10       |
| 27      | -1 | 0  | -1 | 0  | -2 | 12.95      |
| 28      | 0  | 0  | -1 | 0  | -2 | 18.80      |
| 29      | 1  | 0  | -1 | 0  | -2 | 24.90      |
| 30      | 2  | -1 | -1 | 0  | -2 | 26.20      |

The expansion in SUC might be attained while the dye concentration increased from 20 to 100 mg/L. SUC increases while adsorbent levels drop from 0.25 to 0.05 g/L. The graph shown in Fig.3, 5 and 7 suggested that an increase in SUC with an increase in the concentration of dye from 103 to 108.5 mg/L, Contact time varies from 10 to 60 min and temperature varies from 303 to 333 K. A small decrease in SUC could be attained with increase in dose of adsorbent from 0.05 to 0.25g/L and raise in pH from 3 to 10.

Simulation Result using SVM:
This section deals with the simulation result of the SUC for online application. The SVM Network has been developed to find the SUC values. The data set for finding SUC values are generated through experimental results. There are 5 inputs and one output. The input Data set for SVM has five independent most significant factors (pH, adsorbent dosage, dye concentration and agitation speed) decided at five levels (-2, -1, 0, +1, +2). The output is SUC Value. Totally 160 data sets are generated and among these 135 data are for training purpose and the remaining 30 are for testing purpose. SVM models are built using MATLAB software.

The details and performance of SVM model for SUC estimation are presented here. The training time for SVM network is 0.234 sec and the testing error of the SVM network is 0.015 for the user defined gamma and sigma values of 90 and 0.15 respectively. The optimized gamma and sigma values to reach the minimum testing error are identified through trial and error method.

The SVM Network is developed and compared with the actual experimental results. The following table shows the comparison of the predicted and experimental results. The predicted values are almost close to the experimental results and also it shows the accuracy of the proposed model. The SVM Network performance is given in the below table

| No. of Inputs | No. of Output | Control parameter | Training Time | Testing Error |
|---------------|---------------|-------------------|---------------|---------------|
| 5             | 1             | 90                | 0.234         | 0.015         |

Fig. 5. Shows regression plot for SVM Network. The regression structure is drawn between the target values and the predicted network value. Proximity reversal indicates better network performance.

![Error Histogram with 20 Bins](Fig_5.png)

**Fig. 5:** Regression plot for SVM Network.

From Fig. 6, ANN shows a better correlation with the experimental result. Regression value is 0.092 indicating better SVM performance, all output values are applied to the target
Fig. 6: Regression plot for (actual versus predicted)

5. Conclusion

An inexpensive adsorbent obtained from the biomass of corn cob was successfully applied for the elimination of CR dye from the sedimentary solution through the sequential optimization strategy. The statistical approach, which consists of a CCD has been facilitated in to quickly recognizing the significant issues and it also helps to study the interaction between them and determine their ideal values. The ideal values of pH, dye concentration and adsorbent dosage were found to be 7.0, 50 ppm and 0.1g/L respectively for the elimination of CR dye. The test values corresponded well to the model-predicted values. The support vector machine produces more accuracy than Existing Artificial Neural Network..

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