Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2015.1048733

57 (2016) 12281–12286
June

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Taylor & Francis Group

Direct blue 71 dye removal probing by potato peel-based sorbent: applications of artificial intelligent systems

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Received 10 October 2014; Accepted 3 May 2015

ABSTRACT

In this study, the direct blue 71 (DB71) removal efficiency from aqueous solutions by potato peel-based sorbent was examined. Furthermore, influences of five operating parameters including initial pH, sorbent particle size, dose of sorbent, initial dye concentration, and contact time were studied. The Taguchi approach was used to design of experiments. The experiments were performed in a 200-mL batch reactor. Maximum DR% was 90% (448 mg/gr sorption capacity) in initial pH 3, sorbent particle size 225 μm, dose of sorbent 20 g/L, initial dye concentration 100 mg/L, and contact time 10 min. Also, maximum sorption capacity was 1,704 mg/g (85% dye removal) in initial pH 3, sorbent particle size 575 μm, dose of sorbent 5 g/L, initial dye concentration 100 mg/L, and contact time 150 min. The results revealed that the potato peel-based sorbent is promising for the sorption of DB71. After collecting data-set of DR%, artificial neural network (ANN) and genetic algorithm were applied for modeling and optimization of sorption efficiency. The R^2 and root mean square error of the test set were 0.99 and 3.4 for ANN model.

Keywords: Sorption; Potato peels; Design of experiment; Artificial neural networks; Genetic algorithm; Dye removal; Direct blue 71

1. Introduction

Water and wastewater pollutions including toxic or colorful organic materials such as dyes, pesticides, organic solvents as well as toxic inorganic materials especially heavy metals are a great concern in recent years [1–5]. There are several treatment technologies that are developing. Among the numerous treatment technologies, sorption is receiving increasing attention. Different kinds of materials have been applied as the sorbents. Among these materials commercial activated carbons are more effective and applicable. However, the high cost of the activation process limits activated carbon applications in wastewater treatment [6–11].

Over the last few years, a number of investigations have been conducted to explore and to produce low-cost sorbents. The application of agricultural waste masses as raw carbon sources for activated carbon production is presently the most fascinating topic due to low cost and availability that helps the agricultural waste management. In recent studies, several kinds of

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these materials such as fruit and vegetable peels, cone, and leaves have been employed as raw carbon sources [12–14].

Potato peel is disposed as a zero value waste in many countries as part of the production of French fries, crisps, puree, instant potatoes, and similar products. The produced waste ratio and composition depend on the applied steam, abrasion or lye-peeling procedures. Fifteen to forty percent of feed potatoes is waste, which is consisted of 55% of potato skins, 33% starch, and 12% inert material [15,16]. Management of potato peels is a concern of potato industries [17,18].

The objectives of this study were production of potato peel-based sorbent, investigating the ability of potato peel-based sorbent in the removal of the model dye direct blue 71 (DB71) from aqueous solution, application of design of experiment (DoE) to investigate the effects of five operational parameters on the sorption efficiency, and application and assessment of artificial neural network (ANN) and genetic algorithm (Ga) for modeling and optimization the sorption process.

2. Materials and methods

2.1. Regents and instrument

The DB71 dye powder was purchased from Alvansabet Co. (Iran). The chemical structure and characteristics of the DB71 are shown in Table 1. Hydrochloric acid, sulfuric acid, and sodium hydroxide were obtained from Merck. Distilled water for preparation of dye solutions was prepared by a TKA Smart2Pureultra pure water production system (Thermo Electron LED GmbH, Germany). A UV–vis spectrometer model T90$^+$ (PG Instrument Ltd) was used for DB71 analysis by calibration curve method.

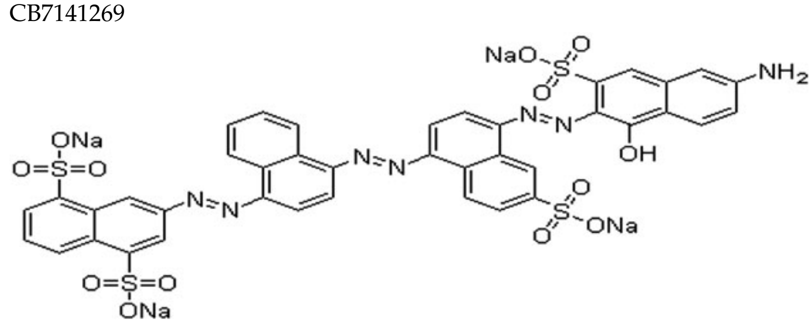
2.2. Sorbent preparation

Potato peels were collected from local restaurant garbage of Kurdistan University of medical sciences. Raw potato peels were washed with hot water to remove adhering dirt. The raw potato peels decolorization was performed by 1 M hydrochloric acid solution. The decolorized potato peels were rinsed with distilled water several times. The prepared potato peels were dried at 70˚C for 48 h. The dried potato peels were crushed by a commercial mill (MKM 6003 model, Bosch company, Germany) and then were sieved through two different sieves sizes with average size of 225 and 575 µm. The obtained sorbent was kept in a seal bottle.

2.3. Design of experiments

In this study, the influences of five operational parameters including average sorbent size (S_Z), initial pH (pH_0), dose of sorbent (D_S), initial dye concentration (C_0), and contact time (t_C) were examined on the DB71 sorption efficiency on the potato peels sorbent. The selected range and levels of these five variables were 225–575 µm for S_Z at two levels, 3–11 for pH_0 at three levels, 10–100 mg/L for C_0 at three levels, 1–10 g/L D_S at three levels, and 10–150 min for t_C at five levels. In order to reduce the number of experiments, randomized order of L_{18} orthogonal array Taguchi design were used for S_Z, pH_0, C_0, and D_S investigation using Minitab 14. In whole 18

Table 1
The chemical properties of DB71

Chemical name	DB71
Molecular formula	$C_{40}H_{23}N_7Na_4O_{13}S_4$
CB number	CB7141269
Molecular structure	
Molecular weight	1,029.86
CAS number	4399-55-7
λ_{max}[a]	522 nm

[a]The maximum absorption wavelength.

Table 2
Details of whole 18 runs that were designed by Taguchi approach

Run	S_Z (μm)	pH_0	C_0 (ppm)	D_S (ppm)	Run	S_Z (μm)	pH_0	C_0 (ppm)	D_S (ppm)
1	225	3	10	1	10	575	3	10	20
2	225	3	50	5	11	575	3	50	1
3	225	3	100	20	12	575	3	100	5
4	225	7	10	1	13	575	7	10	5
5	225	7	50	5	14	575	7	50	20
6	225	7	100	20	15	575	7	100	1
7	225	11	10	5	16	575	11	10	20
8	225	11	50	20	17	575	11	50	1
9	225	11	100	1	18	575	11	100	5

Note: In each run, t_C was investigated at five levels including 10, 30, 60, 90, and 150 min.

experiments, the five levels of t_C were investigated. All the selected experimental conditions presented in Table 2 [19].

2.4. Batch sorption studies

In order to investigate the DR% during the process, the 18 designed experiments were performed in 200-mL batch reactors containing 100 mL of synthetic wastewaters containing desired C_0 (ppm), S_Z, pH_0 and D_S. The experiments were done at room temperature and 150 rpm stirring condition. After determined t_C, each sample was centrifuged at 3,000 rpm. The DB71 dye concentrations were determined based on Beer's law and calibration curve method using a UV–visible spectrophotometer. The wavelength resolution and the bandwidth were 1 and 0.4 nm, respectively. The length of the optical path in glass cell was 1 cm. The maximum absorption wavelength was determined in each runs to prevent the matrix effects. The DB71 concentration data sets were used to calculate the DR % and sorption capacity of the sorbent according to Eqs. (1) and (2).

$$\mathrm{DR\%} = \frac{C_0 - C_t}{C_0} \times 100\ (\%) \tag{1}$$

$$\text{Sorption capacity} = \frac{(C_0 - C_t)}{Ds}\left(\frac{\mathrm{mg}}{\mathrm{g}}\right) \tag{2}$$

where C_0, C_t, and D_S are the initial concentration of DB71, final concentration of DB71, and dose of sorbent in the experiments.

2.5. Methodology of modeling and optimization

The 90 data of DR% together with corresponding experimental conditions were used as a data-set for modeling the process. Two different techniques including ANN and multiple linear regression (MLR) were used to model the process. The five operational parameters were considered as independent variables, whilst the DR% was considered as dependent variable. Data-set was randomly divided into three parts; 60% as a training set, 20% as a validation set, and 20% as testing set. The same training set was used to construct the both models. Since the MLR does not need any validation set, both the validation and test sets were applied as test set in MLR technique. Back propagation algorithm was used for ANN model, since it is very fast and simple. The number of hidden layers and nodes was determined via a trial and error procedure for ANN model. Finally, the quality of the models was determined by some model goodness parameters.

After constructing the models, optimization of process to get higher DR% was performed based on outperformed model. In this study, "Ga" toolbox of MATLAB software was used for generating the optimal solution for maximum DR% [20].

3. Results and discussions

3.1. Sorption process

The results of sorption experiments are presented in Fig. 1. The different diagram in different conditions illustrates the influences of operational parameter. In other word, different levels of experimental parameters cause different DR%. However, statistical analysis should certify the significant influences of each parameter on DR%. In addition, it was found that the potato peel-based sorbent is high-performance sorbent with maximum of 91 DR% and maximum sorbent capacity of 1,704 mg/g.

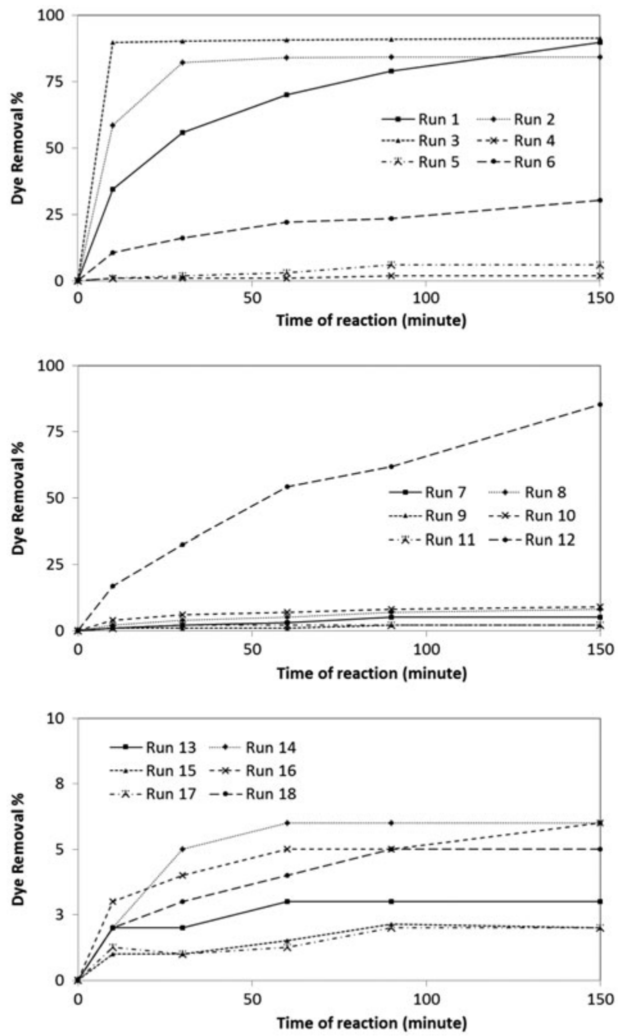


Fig. 1. The obtained DR% of 90 samples and 18 runs.

3.2. MLR modeling

In order to recognize the significant parameters, the MLR modeling approach was applied for DR% modeling. The best obtained model coefficients and related statistical characteristics are presented in Table 3.

Based on unbiased standardized coefficients presented in Table 3, among linear parameters, S_Z and pH_0 have negative influences on DR% but C_0, D_S, and t_C have positive influences on DR%. Also, it can be said that pH_0 and t_C are the most important parameters regarding their larger coefficients. Table 3 indicates that the MLR model does not have good predictability for DR% due to complex mechanism of sorption process. It demonstrates new interest in using more powerful modeling approach, especially ANN model [21–24].

3.3. ANN model

The best ANN model was constructed with five neurons input layer, three neurons hidden layer, and one neuron output layer. The "tansig" transfer function was applied for input and hidden layers and "purelin" for output layer [25]. The model parameters including network weights and biases were adjusted in the ANN model during the network training. Then, the trained network was used to examine the test set. The (5:3:1) ANN model was trained using 54 train data by the back propagation algorithm. The adjusted parameters of trained ANN model were presented in Table 4.

The goodness parameters of the ANN model are presented in Table 5 that shows the high quality of the ANN model in predicting the test set. However, the ANN model is so simple with only three hidden neurons but the ANN model completely outperformed the MLR model. Therefore, the best ANN model was applied to optimize the process conditions to get maximum DR%.

3.4. Ga optimization

Ga optimization process resulted in an optimal solution set to get maximum DR% equal to 91.2%. The

Table 3
The MLR model and related statistical characteristics

	Coefficients	Standardized coefficients	*p*-value
Constant	48.35	None	0.000
S_Z	−0.046	−0.287	0.004
pH_0	−4.795	−0.537	0.000
C_0	0.147	0.201	0.040
D_S	0.375	0.110	0.250
t_C	0.138	0.245	0.013
Data-set	Train (75 data)		Test (51 data)
R^2	0.49		0.49
RMSE	20.2		20.3

Table 4
Network weights and biases of the ANN model

Neuron	Input layer to hidden layer weights					Bias
	S_Z	pH_0	C_0	D_S	t_{SC}	
n_1	−9.05	−3.06	3.24	3.56	0.261	3.629
n_2	7.06	−1.652	−0.231	0.847	0.118	4.95
n_3	0.134	−0.019	−0.067	0.271	19.81	19.25
	Hidden layer to output layer weights					
	n_1	n_2	n_3	bias		
Output	11.16	11.13	9.57	−11.25		

Note: n: neuron or processing elements.

Table 5
Statistical characteristics of ANN model of DR%

Data-set	Train	Validation	Test
R^2	1	0.99	0.99
RMSE	1.1	1.7	3.4

solution values were 418, 3.7, 91, 19, and 45 for S_Z, pH_0, C_0, D_S, and t_C, respectively. The maximum DR% that obtained from GA–ANN approach is so close to the maximum DR% that obtained from the experiments. It approves the ability of ANN approach to model the sorption process. Also it shows that GA approach is successful in getting global optimum. The interpretation of solution values for input variables is given in next paragraphs.

3.5. Influences of S_Z on the DR%

The influences of S_Z were investigated at two levels of S_Z including 225 and 575 μm. The S_Z can influence on two basic parameters of sorption efficiency including adsorption surface area and absorption volume area. Increase in S_Z causes increase in absorption volume area but it causes decrease in adsorption surface area. The ANN–GA optimization approach presents the 418 μm as the optimum value of S_Z [26].

3.6. Influences of pH_0 on DR%

The pH of solution is an important factor that can influence the DR%. Based on the ANN–GA solution, pH_0 of 3.7 is optimum value of pH. The positive influences of acidic media on sorption process are reported frequently. The DB71 dye molecules have hydroxyl, sulfonic, and amine chemical groups that make DB71 dependent to pH. Also, the potato peals-based sorbents have hydroxyl and carboxyl groups that make it dependent to pH. Since both sorbent and sorbate are dependent on pH then there is an optimum pH value. In this optimum pH value, the sorbate and sorbent have opposite charge that helps sorption process [26].

3.7. Influences of C_0 on the DR%

The sorption behavior of DB71 on potato peel-based sorbent was investigated in the range of C_0 (10–100 mg/L) at three levels. Based on ANN–GA optimization approach, the optimum value of C_0 was 91 mg/L. However, increasing C_0 causes increase in DR% until 91 mg/L but more increasing in C_0 does not improve the DR%. It is because of saturation of sorbent sites in higher C_0 than 91 mg/L [26].

3.8. Influences of D_S on the DR%

The D_S influences were investigated in the range of 1–20 mg/L at three levels. As presented in optimal values of empirical parameters, the optimum value of D_S was 19 g/L. It means that DR% increased with the increase in D_S from 1 to 19.0 g/L. More D_S causes more available site for sorption that cause to more DR % [26].

3.9. Influences of t_C on the DR%

The influences of t_C were studied in the range of 0–150 min in five levels. The diagrams of Fig. 1 illustrate that the DR% increased with increasing the t_C until special time and then get stable. The optimum value of 45 min for t_C is in the stable area of the diagrams. The optimum contact time is the time that is needed to get equilibrium [22].

4. Conclusion

The potential of potato peel-based sorbent for the sorption of DB71 from aqueous solution was investigated. The influences of five experimental parameters were studied. The results show the high potential of potato peels to remove the DB71. The high sorption capacity of potato peals-based sorbent is so promising to use it as commercial product in future. Also, producing the high-quality sorbent from potato peels wastes can help the potato peels waste management. This study also shows the ANN modeling technique and GA optimization technique potentials to model and optimize the sorption process.

Acknowledgment

This work was supported by Kurdistan Health Research Center of Kurdistan University of Medical Sciences.

Symbols

$DR\%$	—	dye removal efficiency, percent
pH_0	—	initial pH of dye solution
C_0	—	initial dye concentration, mg/L
C_t	—	initial dye concentration, mg/L
D_S	—	dose of sorbent, g/L
t_C	—	contact time, minute
ANN	—	artificial neural networks
Ga	—	genetic algorithm
RMSE	—	root mean square error

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