

## Statistical assessment of starch removal from starchy wastewater using membrane technology

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**Abstract**—The present work deals with application of  $2^{5-2}$  fractional factorial design (FFD) to evaluate the operating parameters on starch separation from synthetic starchy wastewater using a hydrophilic polyethersulfone membrane with 0.65  $\mu\text{m}$  pore size in a plate and frame handmade membrane module. The analysis of variance (ANOVA) combined with *F-test* was also used to recognize non-significant terms. The performance of the filtration process was evaluated by calculating the COD removal percentage (rejection factor) and permeate flux. In this experiment, five input parameters were surveyed, including trans membrane pressure (TMP), flow and temperature of feed, pH and concentration of wastewater. In this experiment, real wastewater was not used but synthetic starchy wastewater was prepared using starch. Two models were obtained from experimental data, capable of predicting COD removal percentage and permeate flux in different conditions. The predicted values obtained from the regression models were close to the actual ones. For the reduction of fouling, cleaning in place (CIP) method was used.

Key words: Starch, Removal, Membrane, COD, Permeate

### INTRODUCTION

In recent years many investigations have been accomplished for improving the efficiency of starchy wastewater treatment systems in order to achieve stringent discharge standards, from using traditional activated sludge systems, to modern membrane technologies, which are applied in various fields of science and engineering.

One of the advantages of using physical processes in treating wastewater is that there is less need to meet the limited environmental conditions needed to maintain the biological processes performance. On the other hand, using these physical processes is appropriate for those wastewater streams with almost constant properties and quantities, such as industrial wastewater streams, but not the municipal wastewaters, especially those that include storm water and infiltrations in the collection network (combined systems).

Separation processes using membrane technology cannot remove the whole amount of the specified substance from the stream, but instead they can recover and concentrate it simultaneously as a product, so this product can be recycled and reused in the same or other processes [1]. One of the target industries of using this technology can be the starch industries.

In recent years, with respect to the increased price of corn, and greater importance of wheat starch production, an assessment on the wheat starch production process and increasing the efficiency of this process has seemed to be necessary.

Up to now, many investigations have been made on removing starch from wastewater using different kind of membranes and filters. Alazard et al. have studied the treatment of cassava starch extraction wastewater by using an anaerobic horizontal flow filter packed

with bamboo pieces in laboratory scale. The wastewater used in this experimentation was the draining water of the starch sedimentation basin. The maximum organic loading rate was 11.8 g COD/lit·d without dilution of the wastewater. At steady state conditions and maximum organic loading rate, 87% of the inlet COD was removed and a gas productivity of 3.7 lit/lit·d was achieved [2].

Annachatre et al. assessed the performance of an anaerobic pond system for treatment of starch wastewater containing high organic carbon, biodegradable starch particulate matter under tropical climate conditions. Approximately 5,000  $\text{m}^3/\text{d}$  of wastewater from starch industry was treated in a series of anaerobic ponds with a total area of 7.39 ha followed by facultative ponds with an area of 29.11 ha. Overall, COD and TSS removal of over 90% was observed [3].

Movahedian et al. treated the starchy wastewater by using an anaerobic baffled reactor with 13.5 liter volume and hydraulic retention time of 72 hour. In this investigation, the optimum performance was achieved for a retention time of 2.45 day and organic loading of 2.5  $\text{kg}/\text{m}^3\cdot\text{d}$ . In optimum conditions, the COD removal of 67% was reported [4].

Rajasimman et al. used a fluidized bed bioreactor with low density particles to treat high organic concentration wastewater of the starch industry. They tested various COD values (2,250, 4,475, 6,730 and 8,910  $\text{mg}/\text{lit}$ ) and also applied various hydraulic retention times (8, 16, 24, 32 and 40 h). The optimum bed height for the maximum COD removal was found to be 80 cm. At the COD of 2,250  $\text{mg}/\text{lit}$  and the hydraulic retention time of 24 h, the optimum COD removal of 93.8% was reported [5].

Cancino et al. used a hydrophilic polyethersulfone to treat a corn starch wastewater in a pilot test. Their investigation was classified into two types of membrane technologies. First, they processed the wastewater for 4 hours using a microfiltration membrane with a pore size of 0.2  $\mu\text{m}$  at a trans membrane pressure of 250 kPa. The

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permeate contained only 17% of the original wastewater BOD<sub>5</sub>, and the permeate flux achieved during microfiltration was around  $10.8 \times 10^{-6} \text{ m}^3/\text{m}^2 \cdot \text{h}$ . Then, they used a laboratory reverse osmosis module to remove higher amounts of BOD<sub>5</sub>. The permeate flux had only 0.2% of the original wastewater BOD<sub>5</sub> [6].

Sarka et al. investigated the possibilities of recycling the concentrated retentate back to the actual production process using MF and RO membranes. They used a ceramic membrane with a filtration area of  $0.35 \text{ m}^2$  and pore sizes of 500 and 100 nm as MF. Permeate flux above  $100 \text{ lit}/\text{m}^2 \cdot \text{h}$  was achieved for the 100 nm membrane, but the fouling was considerable. The reported COD and BOD<sub>5</sub> removal percentages were approximately 60%. It is noticeable that ceramic membranes are relatively expensive [7].

The main purpose of this research is to study the effect of MF separation on wastewater originating from the starch industry by using a hydrophilic PES membrane with  $0.65 \mu\text{m}$  pore size. This goal is divided into two sections: first, reduction of wastewater pollution, and second, recycling permeates back to the process, leads to reduction of water consumption in production processes.

To reach this goal, the effect of several parameters needs to be investigated. The conventional procedure to study the effects of these parameters is varying one factor and keeping the other factors constant. But using this method, the actual interactions of the parameters cannot be explained, because the interactions between different factors are overlooked, leading to a misinterpretation of the results [8,9]. On the other hand, scientists place a great importance on preventing experimenters from doing so many experiments, which is costly and boring. To avoid doing so, the DoE, which provides a powerful tool preventing doing unnecessary experiments and consider the interactions between factors, was used to optimize the number of tests.

Membrane fouling is the major drawback in membrane processes. Madaeni et al. [10] investigated the effects of trans membrane pressure, cross-flow velocity and feed concentration on cake deposition and consequent fouling in a cross-flow Microfiltration

system. There are several parameters and methods affecting membrane fouling reduction, including feed pretreatment, membrane material, flow manipulation, rotating membranes-high shear filtration, gas sparging, and additional force fields [11]. In this study, physical feed pretreatment and flow manipulation have been used to weaken the fouling effects, such as permeate flux reduction.

To the best of the authors' knowledge, no type of DoE has yet been applied to investigate the rejection factors and the amount of permeate flux in starch separation from starchy wastewaters by using ultra-filtration or micro filtration.

## MATERIALS AND METHODS

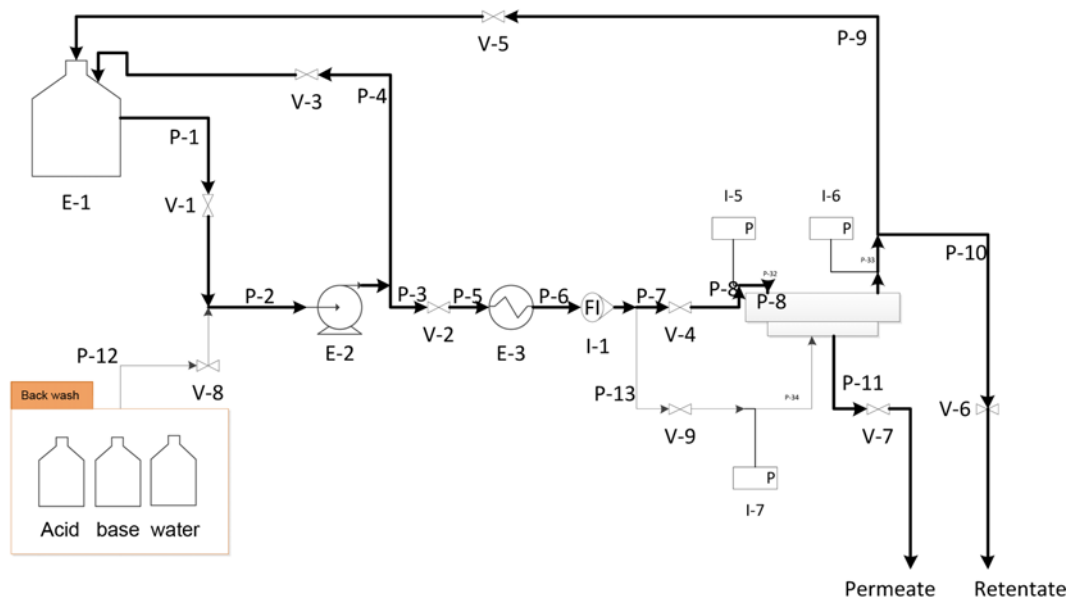
### 1. Materials

The main materials used in this experiment were sodium hydroxide (NaOH), chloridric acid (HCl) and starch (food grade). Synthetic wastewater was prepared using tap water. The plate and frame membrane module was made of steel. The properties of MF flat sheet membranes of hydrophilic polyethersulfone are described in Table 1.

The process flow diagram of the setup is shown in Fig. 1. The unit E-1 represents the tank used to store the feed. To prevent starch settling in the tank a mixer is also installed in it. Using the pipeline P-1, the feed (wastewater) leaves the tank and passes through a valve

**Table 1. Properties of MF flat sheet membranes of hydrophilic polyethersulfone**

Description	Polyethersulfone (PES)
Pore size ( $\mu\text{m}$ )	0.65
Filter size (cm)	$20 \times 20$
Minimum bubble point psi ( $\text{kg}/\text{cm}^2$ )	19 (1.33)
Typical flow rate ( $\text{mL}/\text{min} \cdot \text{cm}^2$ ) @ 10 psi ( $0.7 \text{ kg}/\text{cm}^2$ )	100.875
Maximum operating temperature	$130^\circ\text{C}$ ( $266^\circ\text{C}$ )
pH resistant	1-14



**Fig. 1. The process flow diagram of a starchy wastewater treatment system using a membrane module, and its backwash.**

(V-1) and enters the centrifugal pump with maximum head of 50 m and maximum flow rate of 50 lit/min (E-2). In this study, a range of flow rates needs to be investigated, so the feed is divided into two streams. One is bypassed to the storage tank (P-4), and the other stream enters the heat exchanger (E-3), after passing from a valve (V-2). The effect of temperature on separation of starch by affecting coagulation could be important, so the temperature variations should be studied. By using the heat exchanger mentioned earlier (E-3), the appropriate temperature interval is achieved. The adjusted temperature feed passes through a flow meter with a maximum capacity of 20 lit/min (I-1) and valve (V-4) to enter the plate and frame module, as illustrated.

During the main run, all the back wash related valves (including valve V-9) must be closed. To measure and adjust the operative pressures, two barometers are installed on the feed (I-5) and retentate (I-6) stream. The operative pressure is adjusted by using valves V-4 (inlet pressure) and V-5 (outlet pressure). Trans membrane pressure is calculated by using the following equation:

$$TMP = \frac{P_{in} + P_{out}}{2} \quad (1)$$

The permeate flow leaves the membrane module, passes through the appropriate valve (V-7) and enters the digital flow meter before being stored in the permeate tank for further analysis. The retentate stream recycles to the feed tank, controlled by valve V-5.

## 2. Cleaning Procedure

In the case of membrane fouling, two cleaning procedures can be applied: cleaning in place (CIP) and cleaning out place (COP). The CIP method is the easier and shorter procedure, so in this practice the CIP method was used.

The back wash block in Fig. 1 illustrates the series of backwash tanks including acid, base and water, respectively. The backwash process is divided into three parts (acid, base and water washing), each of them would be in line for 10 minutes. The narrow lines in Fig. 1 represent the backwash stream path. During the backwash process, all the main valves, except those used for both processes (backwash and filtration processes), should be closed, and the backwash valves (V-6, V-8, and V-9) should be opened. Wakeman et al. reported that backwash pressure needs to be greater than the operating filtration pressure [11], so a barometer (I-7) is installed on the permeate side of membrane module to control the backwash stream pressure.

## 3. Experimental Analysis

The performance of the filtration process was evaluated by calculating the COD removal percentage (rejection factor) and permeate flux. Variables which potentially can alter microfiltration process are limited. In this case, the driving force is pressure so pressure has a potent symbol on process performances, especially permeate flux. The other parameter that affects the process performances severely is flow feed because this parameter is in direct relation with surface velocity, which determines the shear tension on membrane surface. Shear tension variations on membrane surface will result in rejection factor and permeate variation by affecting the concentration polarization. In all types of membrane processes, viscosity is an important factor and may affect the entire process, so must be studied. Viscosity is a function of feed concentration, feed temperature and pH. According to the mentioned reasons, filtration per-

formance seems to be dependent on trans membrane pressure, feed flow, feed temperature, pH and starch concentration. In this experiment, the importance of these parameters will be determined by ANOVA table. The COD of the permeate samples was measured by using the STORET NO. 00340 method. Details of the laboratory's instruments and experiments of this measuring method are given in [12].

The COD removal percentage was calculated by using Eq. (2):

$$COD\ Removal\ \% = \left(1 - \frac{COD_p}{COD_f}\right) \times 100 \quad (2)$$

Where  $COD_p$  and  $COD_f$  are chemical oxygen demand in permeate and feed stream, respectively.

The permeate flux was calculated from Eq. (3):

$$J_v = \frac{V}{t \times A} \quad (3)$$

Where V is the volume of the permeate accumulated in time interval t, measured using gravimetric method, and A is the effective area of membrane.

Determining the COD Removal percentage and permeate flux in different conditions to obtain their functionality upon the parameters mentioned above is a very time consuming and costly procedure. To avoid this, an investigation correlation based on experimental design methods is performed, as discussed in next section.

## 4. Experimental Design

Many experiments in several fields of science study the effects of two or more factors. As it was mentioned before, the study of response behavior upon whole factor variations is complicated and time consuming. To resolve this problem, factorial design methods are used to investigate all possible combinations of the factors involved in the experiment [13]. As a powerful statistical and mathematical tool, factorial design helps identify the effective factors, study interactions, select optimum conditions and the vital input factors in limited number of experiments [14]. In fact the two-level factorial design is one of the design of experiment methods, which is applied in this study.

Two-level factorial design is divided into two subcategories, including full factorial and fractional factorial design. In two-level full factorial design,  $2^k$  runs must be fulfilled, where k runs are related to primary effects and the rest are related to two, three and higher factor-interactions [13]. In fact, this method investigates all effects (main effects and interactions). By increasing the number of factors, the number of runs will also increase rapidly, even if these terms have no effect on responses, and this is one of the drawbacks of two-level full factorial design [15]. The other drawback of the two-level factorial design is its weakness in elaborating curvatures.

To avoid the first disadvantage of full factorial design mentioned above, high-order interactions should be neglected, so information about main effects and lower-order interactions will become more sensible. This method is called fractional factorial design. In fact, it is a method used to screen the least important factors. By this way, the factors that have no or low effect on responses are removed, which leads to a reduction of the number of factors.

There are several statistical softwares used for fractional factorial design analysis. The one which is used in this research is the Design Expert and the related diagrams were plotted using MAT-

**Table 2. Processing input variable parameters involved in fractional factorial design (FFD)**

Process variables	Unit	Code	Low level	High level	Variation interval
Trans membrane pressure (TMP)	Bar	A	1	2.5	1.5
Feed flow	lit/min	B	4	11	7
Feed temperature	Centigrade	C	20	60	40
pH		D	6.5	11	4.5
Concentration	g/lit	E	1	5	4

LAB program.

The present work deals with application of design of experiment (DoE) and fractional factorial Design (FFD) for modeling of starch removal from starchy wastewater using micro-filtration in a plate and frame homemade membrane module. The two-level fractional factorial design (FFD) was employed to set the input variable parameters which are shown in Table 2, and the analysis of variance (ANOVA) combined with F-test was used to differentiate non-significant and significant terms.

In the factorial design of experiments, if the response factors and the input variable are continuous, finding a mathematical model for the responses in terms of the input variable factors is useful; and if there is no continuous link between the responses and the levels of a factor, considering a comparison of the response in terms of two levels of a qualitative factor is useful [16].

Design Expert deals with coded values. This program gets the inputs in both coded and actual values, processes the data in coded form and displays the output formula in both coded and actual values.

By coding the input variables in the fractional factorial design (FFD), the coded variables can be evaluated as below [17]:

$$x_j = \frac{\tilde{x}_{j,high} - \tilde{x}_{j,low}}{i_j} \quad (4)$$

Where

$$\tilde{x}_{j0} = \frac{\tilde{x}_{j,high} + \tilde{x}_{j,low}}{2} \quad (5)$$

$$i_j = \frac{\tilde{x}_{j,high} - \tilde{x}_{j,low}}{2} \quad (6)$$

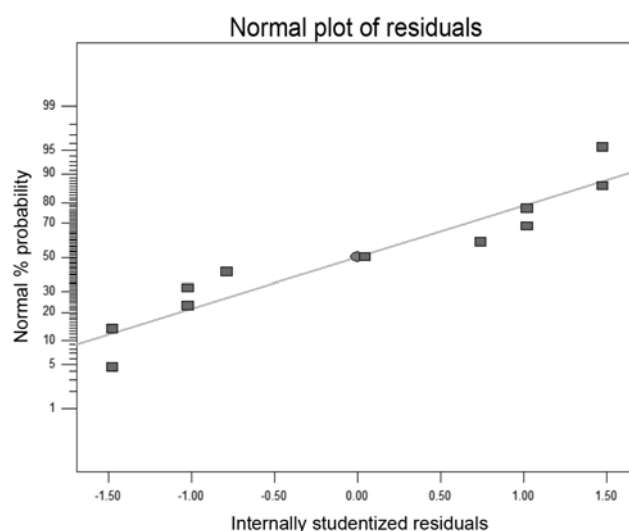
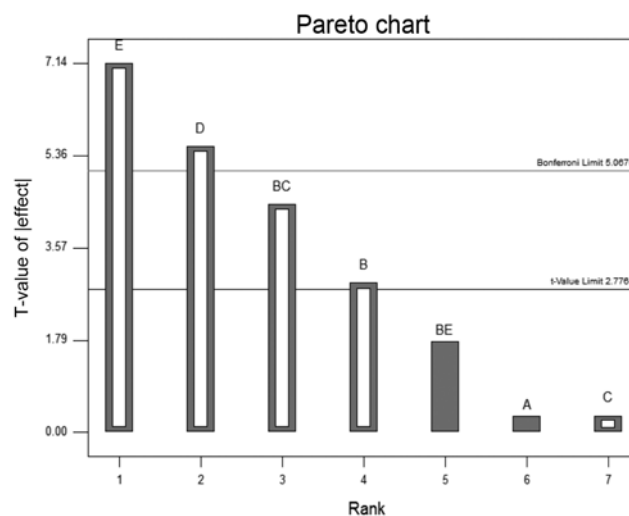
**Table 3. The experimental runs layout and the experimental results of two-level fractional factorial design (FFD)**

Run number	A	B	C	D	E	Rejection factor (%)	Permeate flux (lit/min·m <sup>2</sup> )
1	–	–	–	+	+	97.3	0.73
2	+	–	–	–	–	95.0	4.99
3	–	+	–	–	+	98.7	3.00
4	+	+	–	+	–	91.7	3.89
5	–	–	+	+	–	89.2	0.37
6	+	–	+	–	+	98.0	1.04
7	–	+	+	–	–	98.3	2.98
8	+	+	+	+	+	98.0	0.67
9	0	0	0	0	0	97.8	1.13
10	0	0	0	0	0	98.3	1.41
11	0	0	0	0	0	97.2	1.64

$\tilde{x}_{j,high}$  and  $\tilde{x}_{j,low}$  are the actual value of the high level and low level of each input variables, respectively. A  $2^{5-2}$  fractional factorial design with three replicates at the center point for determining the pure error was planned.

## RESULTS AND DISCUSSION

In this section, the analysis of variances of rejection factor and

**Fig. 2. Normal porability plot vs. internally studentized residuals for COD removal.****Fig. 3. Pareto chart for COD removal.**

**Table 4. ANOVA test for selected factorial model for rejection factor percentage-analysis of variance table (Partial sum of squares- Type III)**

Source	Sum of squares	Df	Mean squares	F-value	P-value Prob>F	Comment
Model	85.09	5	17.02	21.91	0.0052	Significant
B-flow	6.48	1	6.48	8.34	0.0446	
C-temperature	0.08	1	0.080	0.10	0.7643	
D-pH	23.81	1	23.81	30.65	0.0052	
E-concentration	39.60	1	39.60	50.99	0.0020	
BC	15.12	1	15.12	19.47	0.0116	Significant
Curvature	8.65	1	8.65	11.14	0.0289	
Residual	3.11	4	0.78			Not significant
Lack of fit	2.50	2	1.25	4.12	0.1953	
Pure error	0.61	2	0.30			
Cor total	96.86	10				

permeate flux is performed and the regression models and related tables and plots are introduced. The test configurations and experimental results of two-level fractional factorial design (FFD) are summarized in Table 3.

The normal probability plot illustrated in Fig. 2 indicates whether the residuals follow a normal distribution or not. In the normal distribution, the points will follow a straight line. Definite patterns like an “S-shaped” curve indicate that a response transformation may provide a better analysis.

Fig. 3 illustrates a Pareto chart of the selected effects. The Pareto chart is a useful graphical tool for showing the relative size of effects. In analyzing this chart, the effects would be divided into three categories:

1. Effects that are located above the Bonferroni Limit are certainly significant.
2. Effects that are located above the t-value Limit and below the Bonferroni Limit are possibly significant.
3. Effects that are located below the t-value Limit are not likely to be significant.

With respect to these definitions, effects E (concentration) and D (pH) are significant and effects BC (Flow×Temperature) and B (Flow) are possibly significant.

In the ANOVA table, The *P-values* were used as a tool to check the significance of each of the coefficients, which, in turn, are necessary to understand the pattern of the mutual interactions between the test variables [18]. Values of *Prob>F* less than 0.0500 indicate model terms are significant, and values greater than 0.1000 indicate the model terms are not significant. According to the ANOVA test in Table 4 and Pareto chart illustrated in Fig. 3, the main effects including pH (D) and concentration (E) affect the COD removal percentage and there is a significant interaction between flow and temperature in the model. The main effects of flow (B) and temperature (C) are not significant terms, but to present a hierarchic model, these are included in the model. As Gheshlaghi et al. said, model hierarchy maintains the relationships between main and interaction effects, so models derived in terms of real values from non-hierarchically coded models are incorrect models [15].

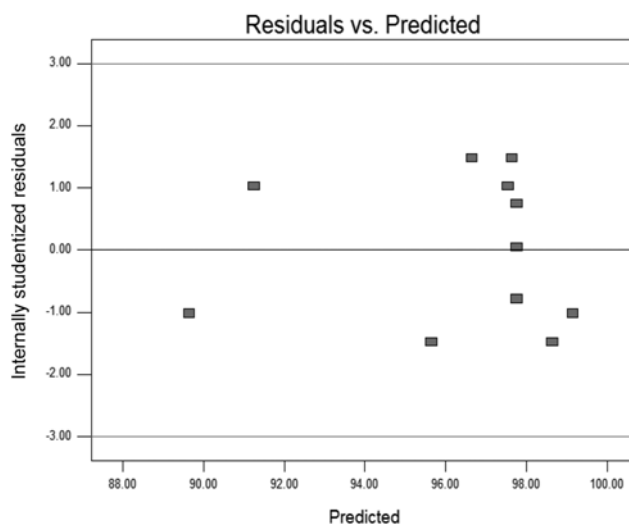
“Adeq Precision” measures the signal to noise ratio. This parameter compares the range of the predicted values at the design points to the average prediction error [19]. A ratio greater than 4 is desir-

able. In this study, a ratio of 8.387 for COD Removal indicates an adequate signal. This model can be used to navigate the design space.

The Model *F-value* of 7.24 implies the model is significant. There is only a 2.44% chance that a Model *F-Value* this large could occur

**Table 5. Comparison of model prediction with plant experimental data for COD removal percentage**

Standard order	Actual value (%)	Predicted value (%)
1	97.3	97.2
2	95.0	96.2
3	98.7	99.7
4	91.7	91.8
5	89.2	90.2
6	98.0	98.1
7	98.3	98.2
8	98.0	99.2
9	97.8	96.1
10	98.3	96.1
11	97.2	96.1

**Fig. 4. Studentised residual for COD removal based on.**

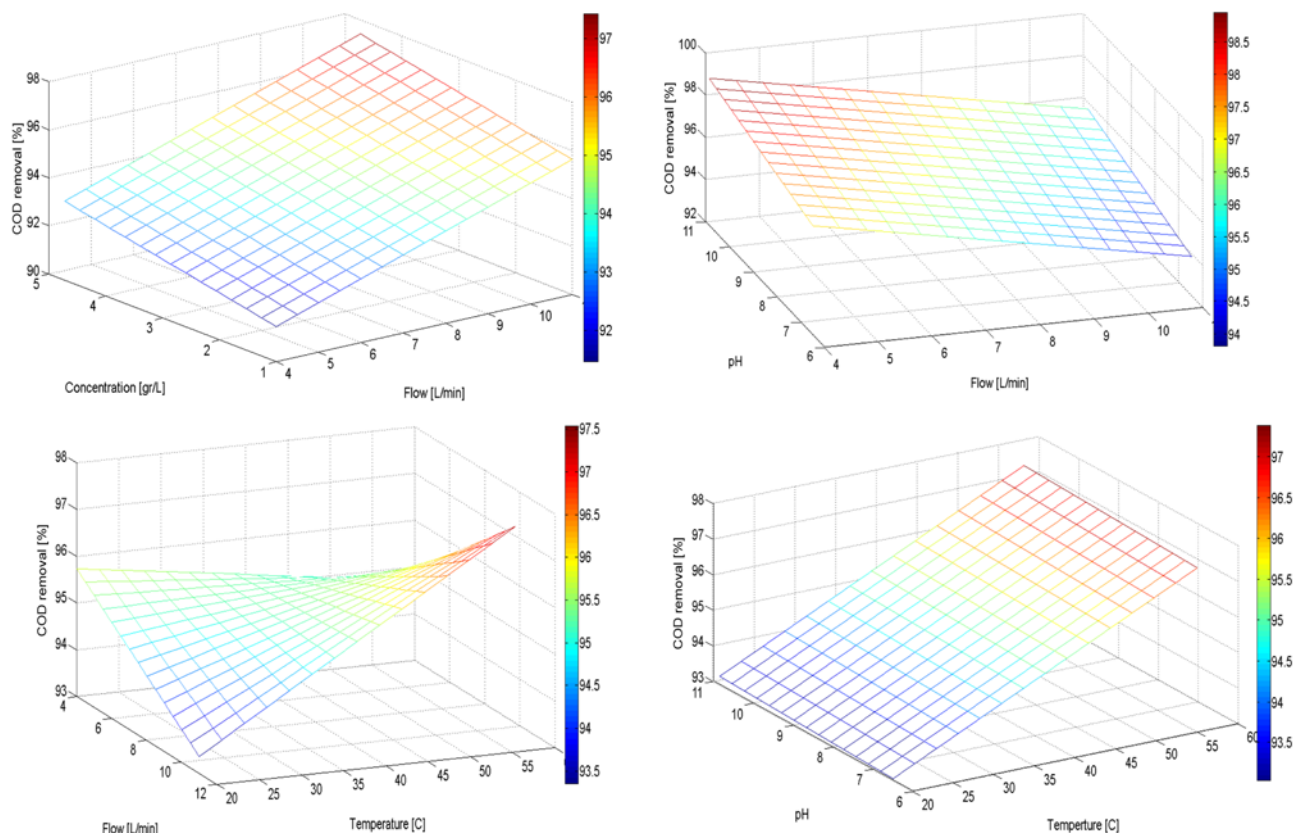


Fig. 5. Rejection factor diagrams in 4 cases.

due to noise.

The goodness of the model can be checked by determination of coefficient  $R^2$  and adjusted  $R^2$  [8]. In this study, for COD Removal,  $R^2$  is 0.8786 implies that 87.86% of the response variability is achieved by the regression model. The adjusted  $R^2$  is 0.7571. The curvature  $F$ -value of 0.0289 implies that the curvature is significant.

Final equation for COD Removal percentage in terms of coded factors that obtained from regression of values is as below:

$$\text{COD Removal \%} = 96.32 + 0.90 \times B + 0.10 \times C - 1.73 \times D + 2.22 \times E + 1.37 \times B \times C \quad (7)$$

Expressing the response in actual values is preferred. So, by con-

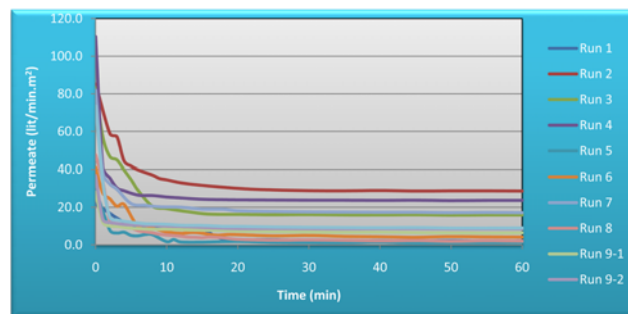


Fig. 6. Permeate flux vs. time for all 11 runs.

Table 6. ANOVA test for selected factorial model for permeate flux-analysis of variance table (Partial sum of squares- Type III)

Source	Sum of squares	Df	Mean squares	F-value	P-value	Comment
Model	20.90	5	4.18	56.92	0.0008	Significant
A-pressure	1.54	1	1.54	20.92	0.0102	
B-flow	1.46	1	1.46	19.83	0.0112	
C-temperature	7.12	1	7.12	96.91	0.0006	
D-pH	5.04	1	5.04	68.68	0.0012	
E-concentration	5.75	1	5.75	78.26	0.0009	
Curvature	1.46	1	1.46	19.83	0.0112	Significant
Residual	0.29	4	0.073			
Lack of fit	0.17	2	0.083	1.30	0.4352	Not significant
Pure error	0.13	2	0.064			
Cor total	22.65	10				

verting coded values in Eq. (7) to actual values using Eq. (4), the following equation achieved:

$$\begin{aligned} \text{COD Removal \%} = & 103.45330 - 0.52857 \times \text{Flow} - 0.14232 \\ & \times \text{Temperature} - 0.76667 \times \text{pH} + 1.11250 \\ & \times \text{Concentration} + 0.01964 \times \text{Flow} \times \text{Temperature} \quad (8) \end{aligned}$$

As represented in Eq. (7) and Eq. (8), there are four linear and one interaction terms plus a constant term in the regression model. All main effects except concentration (E) have negative effects and the unique interaction between flow (B) and temperature (C) has a positive effect.

A comparison between the actual and predicted values of COD removal is illustrated in Table 5 and the assumption of constant variance was tested at Fig. 4 by plotting the studentised residual vs. predicted response as obtained from the model. In Fig. 5, the COD Removal percentage plot versus operating parameters in 4 cases is illustrated. It is noticeable that these graphs are drawn in according to Eq. (8) by changing two parameters and keeping the other parameters constant in each case.

Fig. 6, illustrated the permeate flux vs. time for 11 runs. As it can be seen, each run continues to 1 hour and approximately after 30 minutes the permeate flux would be constant.

The mean permeate flux was calculated by the Eq. (9).

$$\text{permeate flux} = \frac{1}{t_N - t_0} \int_{t_0}^{t_N} F \cdot dt \quad (9)$$

Where  $t_N$  is the overall time of each run and  $F$  is the permeate flux

**Table 7. Comparison of model prediction with plant experimental data for permeate flux**

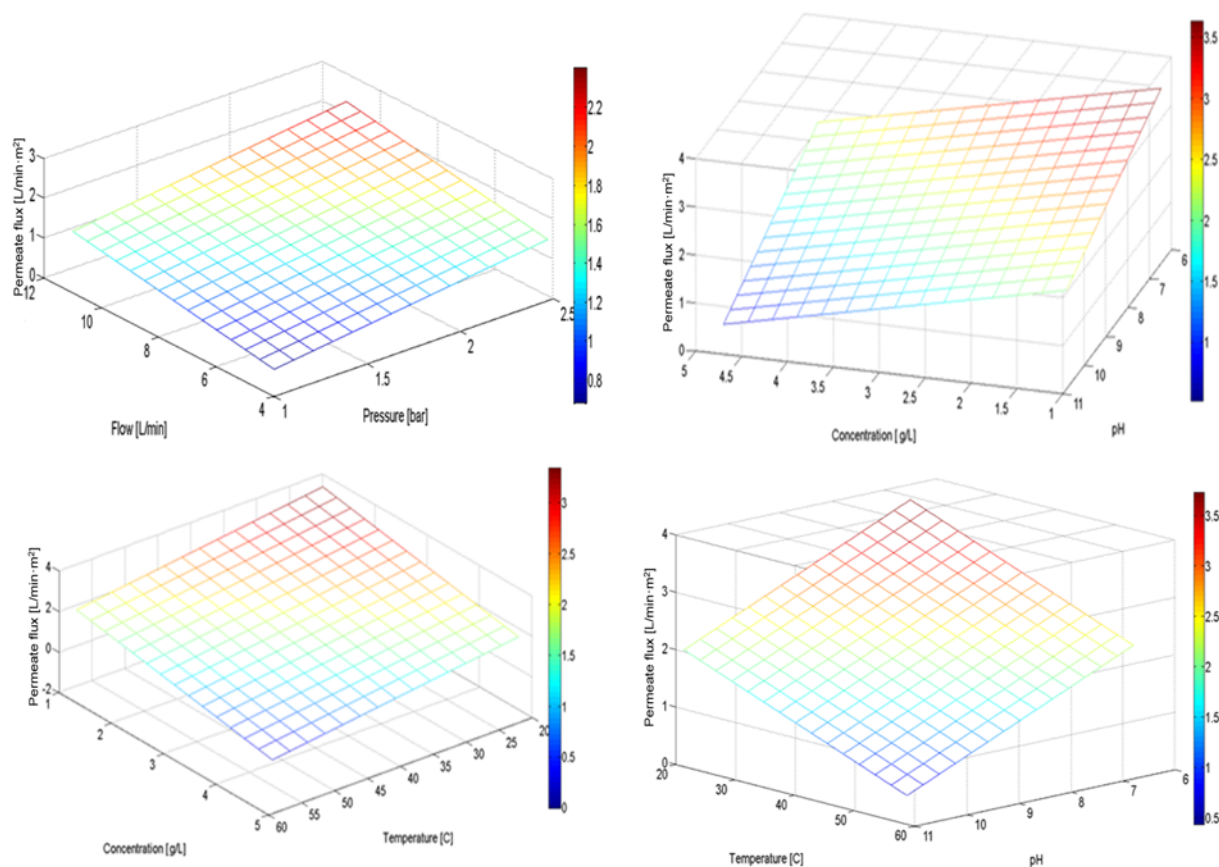
Standard order	Actual value (lit/min·m <sup>2</sup> )	Predicted value (lit/min·m <sup>2</sup> )
1	0.73	0.42
2	4.99	4.58
3	3.00	2.86
4	3.89	3.85
5	0.37	0.23
6	1.04	1.00
7	2.98	2.67
8	0.67	0.27
9	1.13	1.90
10	1.41	1.90
11	1.64	1.90

at time  $t$ . The integral was calculated by the trapezoidal method, and mean permeate flux of each run is presented in Table 7 as actual value.

The same method was used to analyze the COD removal was applied for analysis of permeate flux. The ANOVA table is illustrated in Table 6. In the analysis of the values related to permeate flux, the R-squared is 0.9227 and the adjusted R-squared is 0.8455.

The permeate flux in coded factor is as below:

$$\text{Permeate Flux} = 1.99 + 0.44 \times A + 0.43 \times B - 0.94 \times C$$



**Fig. 7. Permeate flux diagrams in 4 cases.**



**Table 8. Optimum condition**

Pressure [bar]	Flow [lit/min]	Temperature [°C]	pH	Concentration [g/lit]	Rejection factor (%)	Permeate flux (lit/m <sup>2</sup> ·min)	Desirability
2.50	11.00	20.11	6.50	4.09	98.7	4.12	0.901

$$-0.79 \times D - 0.85 \times E \quad (10)$$

It is noticeable that all of the factors are in two levels, 0 or 1.

By converting the coded factors to actual values by using Eq. (4), the following equation is obtained:

$$\begin{aligned} \text{Permeate Flux} = & 6.29632 + 0.58425 \times \text{Pressure} \\ & + 0.12191 \times \text{Flow} - 0.047162 \times \text{Temperature} \\ & - 0.35292 \times \text{pH} - 0.42382 \times \text{Concentration} \end{aligned} \quad (11)$$

The related diagram obtained from Eq. (11) is illustrated in Fig. 7. As the Eq. (10) and Eq. (11) and the ANOVA table have expressed, all of the input variables have significant effect on the permeate flux.

As mentioned earlier, finding the optimum condition is so important because by running the filtration system on the basis of optimum condition the performance of membrane filtration will be the best one. In this case, optimum condition is a state that both rejection factor and permeate flux have the possible largest value. One of the useful approaches to optimize the multiple responses is to use the simultaneous optimization techniques by applying the created mathematical models. The desirability function approach is one of the most widely used methods in optimizing multiple response processes. The general approach is, first conversion of each response  $y_i$  into an individual desirability function  $d_i$ , which varies over the following range:

$$0 \leq d_i \leq 1$$

Where if the response  $y_i$  is at its goal or target, then  $d_i=1$ , and if the response is outside an acceptable region,  $d_i=0$ . Then the design variables are chosen to maximize the overall desirability as follows:

$$K = (d_1 \cdot d_2 \cdot \dots \cdot d_m)^{1/m}$$

Where  $m$  is the number of responses [13].

The Design Expert software finds optimum condition using the desirability function approach. The optimum condition for this process is presented in Table 8.

## CONCLUSION

This article deals with studies on starch removal from starchy wastewater by PES microfiltration in a plate and frame module. To screen the effective parameters and find the correlation for COD removal and permeate flux with minimum tests, fractional factorial design was applied. A  $2^{5-2}$  fractional factorial design combined with three center-points was devised. The analysis of variance (ANOVA) was performed and two regression models for COD removal percentage and permeate flux were obtained from data. The predicted values are approximately close to actual values. The permeate stream

(treated wastewater) may be recycled to the production line and decreases the water consumption of starch production but discharging it to the environment is dependent upon local environmental regulation which vary from one country to another. In most cases, the properties of treated wastewater coincide with environmental regulation and it can be discharged to environment.

## REFERENCES

1. I. Ortiz, Sergio M. Corvalan and A. M. Eliceche, *Comput. Chem. Eng.*, **555** (2002).
2. D. Alazard, X. Colin, J.-L. Farinet and O. Rojas, *Bioresour. Technol.*, **98**, 1602 (2007).
3. A. P. Annachatre and B. K. Rajbhandri, *Bioresour. Technol.*, **95**, 135 (2004).
4. H. Movahedyan, A. Assadi and A. Parvaresh, *Iran J. Environ. Health Sci. Eng.*, **2**, 77 (2007).
5. M. Rajasimman and C. Karthikeyan, *J. Hazard. Mater.*, **143**, 82 (2007).
6. B. Cancino, F. Rossier and C. Orellana, *Desalination*, **200**, 750 (2006).
7. E. Sarka, V. Pour, A. Vesela and Z. Bubnik, *Desalination*, **249**, 135 (2009).
8. S. Mannan, A. Fakhru'l-Razi and Md Zahangir Alam, *J. Environ. Sci.*, **19**, 23 (2007).
9. M. Ziabari, V. Mottaghitalab and A. K. Haghi, *Korean J. Chem. Eng.*, **27**, 340 (2010).
10. S. S. Madaeni, M. Rahimi and M. Abolhasani, *Korean J. Chem. Eng.*, **27**, 206 (2010).
11. R. J. Wakeman and C. J. Williams, *Sep. Purif. Technol.*, **26**, 3 (2002).
12. R. E. Crowe and D. G. Ballinger, *Manual of methods for chemical analysis of water and wastes*, EPA, Cincinnati, Ohio (1976).
13. Montgomery, Douglas C, *Design and analysis of experiments*, 5<sup>th</sup> Ed., Wiley, New York (2001).
14. J.-D. Cui, *Korean J. Chem. Eng.*, **27**, 174 (2010).
15. R. Gheshlaghi, J. M. Scharer, M. Moo-young and P. L. Douglas, *Anal. Biochem.*, **383**, 93 (2008).
16. S.-H. Lin, C.-L. Hung and R.-S. Juang, *Desalination*, **234**, 116 (2008).
17. Ioannis Xiarchos, Agnieszka Jaworska and Grazyan Zakrzewska-Trznadel, *J. Membr. Sci.*, **321**, 222 (2008).
18. R. S. Singhal, K. M. Desai, S. A. Surveys, P. S. Saudagar and S. S. Lele, *Biochem. Eng. J.*, **41**, 266 (2008).
19. A. Idris, F. Kormin and M. Y. Noordin, *Sep. Purif. Technol.*, **49**, 271 (2006).