ARTIFICIAL NEURAL NETWORK BASED MODELING OF MICROFILTRATION PROCESS FOR WHEY PROTEIN CONCENTRATION

A PROJECT REPORT

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

MASTERS IN SCIENCE
IN
BIOTECHNOLOGY

Submitted by

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JUNE 2024

ACKNOWLEDGEMENT

In gratitude for all your contribution to this project thesis, I wish to extend my deepest thank to each of you.

I would like to first and foremost gratitude goes to my supervisors Prof. Jai Gopal Sharma, Prof. in the Department of Biotechnology, Delhi Technological University, Delhi and Dr. Manish Jain from the Department of Chemistry , Delhi Technological University, Delhi for supporting, encouraging, and guiding me throughout in my project. Throughout this project, their expertise, insights, and feedback played an important role.

I also want to thank Prof. Yasha Hasija, Head of Department for providing me with the department facilities and resources that I needed to complete my research effectively. I am also grateful to the faculty members of the Department of Biotechnology, Delhi Technological University, they helped me a lot with my thesis, and their opinions and advice helped me make the ideas stringer and the work better as a whole

I am equally thankful and wish to express my wholehearted thanks to respected lab senior Ms. Megha Bansal for her support and help in the course of my thesis work. I would wish to express my gratitude and affection to my family for their constant love and support.

Finally, I would like to recognize and thank Delhi Technological University for providing me with the teaching environments, tools, and facilities I needed to learn. What I learned and did at this well-known university has had a big impact on my both academic as well as professional routes.

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CANDIDATE'S DECLARATION

I, **PRAFFUL KUMAR MEENA (2K22/MSCBIO/39),** hereby declare that the project entitled **"ARTIFICIAL NEURAL NETWORK BASED MODELING OF MICROFILTRATION PROCESS FOR WHEY PROTEIN CONCENTRATION"** which is submitted by us to the Department of Biotechnology, Delhi Technological University, Delhi is a record of the project work carried out by us under the supervision of Prof. Jai Gopal Sharma and Dr. Manish Jain in partial fulfilment of the requirement for the award of the degree of Master of Science, is original and not copied from any source without proper citation. To the best of our knowledge and belief, this work has not been previously submitted for the award of any degree or diploma to any other University or Institution.

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CERTIFICATE BY THE SUPERVISOR

I, hereby certify that the Project Dissertation titled, **"ARTIFICIAL NEURAL NETWORK BASED MODELING OF MICROFILTRATION PROCESS FOR WHEY PROTEIN CONCENTRATION**" which is submitted by **PRAFFUL KUMAR MEENA[2K22/MSCBIO/39]**, Department of Biotechnology, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Science, is a record for the Project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Microfiltration is one of the most suitable processes for protein recovery from whey due to low energy consumption and no use of heat and chemicals. However, membrane fouling is one of the limiting factors in the microfiltration process preventing its commercial use. In this study, an Artificial Neural Network (ANN) based model was employed to study the effects of different operating parameters on the membrane fouling in whey concentration. Transmembrane pressure, Reynolds number, and temperature of feed were selected as the input parameters. Experimental data from the available studies were used to train ANN. ANN with 23 neurons gave minimum mean squared error (MSE) for trans-membrane pressure and Reynolds number. ANN with 7 neurons gave minimum MSE for feed temperature. Predicted values from both ANNs well fitted with the experimental results with R2 < 0.99. Simulations showed that membrane fouling increased as flux reduction increased from 36.3 % to 76.39 % when trans-membrane pressure increased from 0.5 to 2 bar. While a 19.96 % reduction in flux was observed by increasing the Reynolds number from 750 to 2500. An increment of 77.37 % of flux was observed with increasing feed temperature from 30 ºC 40 ºC. Simulations confirmed that trans-membrane pressure, Reynolds number, and temperature of feed all three operating parameters strongly influence the membrane fouling. ANN based approach was found most accurate results in comparison to theoretical models. Among all theoretical models, the intermediate blocking model gave the most accurate results with a mean relative error of 0.185.

LIST OF PUBLICATIONS

1. Poster Presented at International Conference on Basic, Analytical and Allied Sciences at the Interface of Carbohydrates and Biomass Valorisation Organised by the Department of Applied Chemistry, Delhi Technological University in association with the Association of Carbohydrate Chemicals and Technologies (India) from 30th November to 2nd December 2023.

2. Poster Presented at the International Desalination Environment and Sustainability (IDEAS) Conference 2024 Organised by Water Research Centre (NYUAD-WRC), The New York University, Abu Dhabi Campus, from 22nd January to 23rd January 2024.

3. Journal Paper "Recovery of whey protein by using microfiltration: Artificial Neural Network based modeling and effects of different operating parameters" in review in Journal of Food Process Engineering (Manuscript No: JFPE-2024-Jun-0603) (Publisher: Wiley; Indexing: SCIE, Scopus)

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER- 1
INTRODUCTION

Whey is a by-product of the cheese production industry, containing mainly water (93 to 94%), lactase, milk proteins, lactic acids, fats, citric acid, other nitrogen compounds, and vitamins (B group) [1, 2]. In the past, whey was considered waste and either used as animal feed, spared in fields as fertilizers, or disposed of as waste [1]. However, because the biological oxygen demand of whey ranges from 35000 mg/l to 55,000 mg/l [1], disposal of whey in any water body without any treatment may lead to major environmental issues. Moreover, compounds present in the whey as described above have high nutritional values, mainly lactose, amino acids, proteins, minerals, and vitamins [3], and are used in several food processing industries. Therefore, recovery of these compounds from whey efficiently and economically becomes a major challenge for the worldwide dairy industry [1-3].

Several processes can be used to concentrate or recover the various nutrients from whey such as drying using evaporation, crystallization of lactose, heat precipitation or coagulation of whey proteins, chromatographic separation of whey proteins, and membrane-based separation processes [1]. However, heat-based thermal processes such as drying and thermal coagulation may alter the molecular structure of the whey protein. Moreover, these processes are highly energy-consuming processes. On the other hand, chromatographic processes are only suitable for lab-scale operations and difficult to scale up for industrial-scale production [1,3]. Membrane-based separation processes are more useful as these processes work at room temperature. Furthermore, different membrane-based processes can be used for a variety of operations. For example, whey solids can be concentrated by using reverse osmosis and nano-filtration. Lactose can be separated and concentrated by nanofiltration and different proteins and lipids can be separated, concentrated, and purified through ultrafiltration and microfiltration [1-3]. In this study, microfiltration is investigated for the separation/concentration of whey proteins.

A number of experimental studies are available on the separation of different whey components [4-19]. G. Gsan et. al [4] analyzed the effects of operating conditions on microfiltration performance for the separation of whey proteins. They found that operating conditions such as rate of change of permeation flux, tangential flow, and magnitude of wall shear stress have profound effects on membrane fouling and thus overall performance of the microfiltration. An instantaneous change in permeation flux leads to better protein transmission while also resulting in lower permeate flux in comparison to a gradual change in permeate flux. In a similar study, G. Gsan et. al [5] investigated the effects of trans-membrane pressure gradient and transient operating conditions on membrane fouling. Their experiments showed that the dynamic counter-pressure mode of operation gives lower fouling, longer operational time, and higher protein recovery than the static pressure mode. S.T. Kelly et. al [6] compared the fouling behavior of different kinds of model proteins present in the whey. MarijanaĐ. Carić et. al [7] studied the fouling of inorganic membranes for whey protein separation and concluded that the adsorption-related pore-plugging mechanism dominates the process.

Blanpain-Avet et. al [8] investigated the effects of multiple fouling and cleaning cycles on the performance of ceramic microfiltration membranes for whey protein separation. They concluded that hydraulic cleaning is not sufficient for recycling the membranes. Effects of different process parameters such as cross-membrane pressure, feed temperature, feed flow rate, feed pH, and feed concentrations on membrane fouling and membrane performance for whey protein separation were also investigated in a number of studies [9-19]. All of the above-mentioned studies [4-19] suggest that membrane fouling is an important phenomenon in the case of whey processing using a microfiltration process. Moreover, it also depends on multiple factors including membrane characteristics, operating parameters, and feed composition [4-19]. This makes the study of membrane fouling an important aspect of commercializing microfiltration for whey processing.

Membrane fouling in microfiltration is generally modeled by different mechanisms based on how particles present in the feed block the membrane's pore. The main models include the cake filtration model, intermediate blockage model, standard blockage model, and complete blockage model [20, 21]. The mathematical expression of all of these models contains constants that are determined by experimental results of fouling tests conducted in either constant pressure mode or constant flux mode [20, 21]. However, these models do not represent the effects of different factors such as membrane characteristics, operating parameters such as feed temperature, cross-membrane pressure feed flow rate, and feed composition on membrane fouling. Effects of all these parameters on membrane fouling are very complex phenomena and difficult to model by traditional transport models or empirical models. The Artificial Neural Network (ANN) based MODELING approach is very useful for such problems. ANN mimics the working human brain to determine the inherent correlations between the input and output parameters based on experience or available experimental results [22-24].

This study focused on analyzing the effects of different operating parameters including the effects of trans-membrane pressure, feed flow rate, and feed temperature on flux at different intervals of the operations. First, the experimental results from the different studies [11, 17] were used to train, validate and test the ANN. The number of neurons in ANN was also optimized to reduce the mean squared error between experimental results and ANN predictions. The system was also modeled with traditional models to compare the efficiency of trained ANN concerning traditional models. Trained ANN was then used to determine the effects of different operating parameters on the whey protein separation.

CHAPTER 2
THEORY

2.1 Microfiltration process and membrane fouling

A schematic diagram of a microfiltration process is shown in Figure 1. It is a pressure-driven membrane-based filtration process, used to separate microparticles from a liquid suspension. Microfiltration membranes are generally made of polymeric or ceramic materials having a pore size of more than 100,000 Da [20]. On the other hand, ultrafiltration membranes have pore sizes between 1000 Da to 100,000 Da and can be used to separate smaller particles. In a cross-flow microfiltration process feed enters at the one end of the feed channel at high pressures. Solvent molecules permeate through the porous membrane due to the trans-membrane pressure difference and at last, the remaining concentrated retentate solution comes out from the other end of the feed channel [34].

During cross-flow microfiltration, some of the solute particles are also forced towards the membrane surface in the feed section with solvent. However, as membrane pores size are less these particles may be adsorbed on the surface of the membrane or inside the membrane pores. This causes a continuous reduction of the permeate flux, which prevents running the microfiltration process for a longer time in continuous mode [20, 21]. Thus, the microfiltration membranes need to be regenerated after some time to remove the membrane fouling and increase the trans-membrane flux. The regeneration process is done by backwashing and/or by using different chemicals. However, all fouling may remain permanent and cannot be removed during the regeneration process. Thus, membrane fouling is an important and limiting phenomenon in the microfiltration process [20, 21]. The microfiltration process can only be commercialized for a given feed system when fouling can be controlled and the membrane can be regenerated. Therefore, studying membrane fouling is an important step in investigating the viability of the microfiltration process for a particular system.

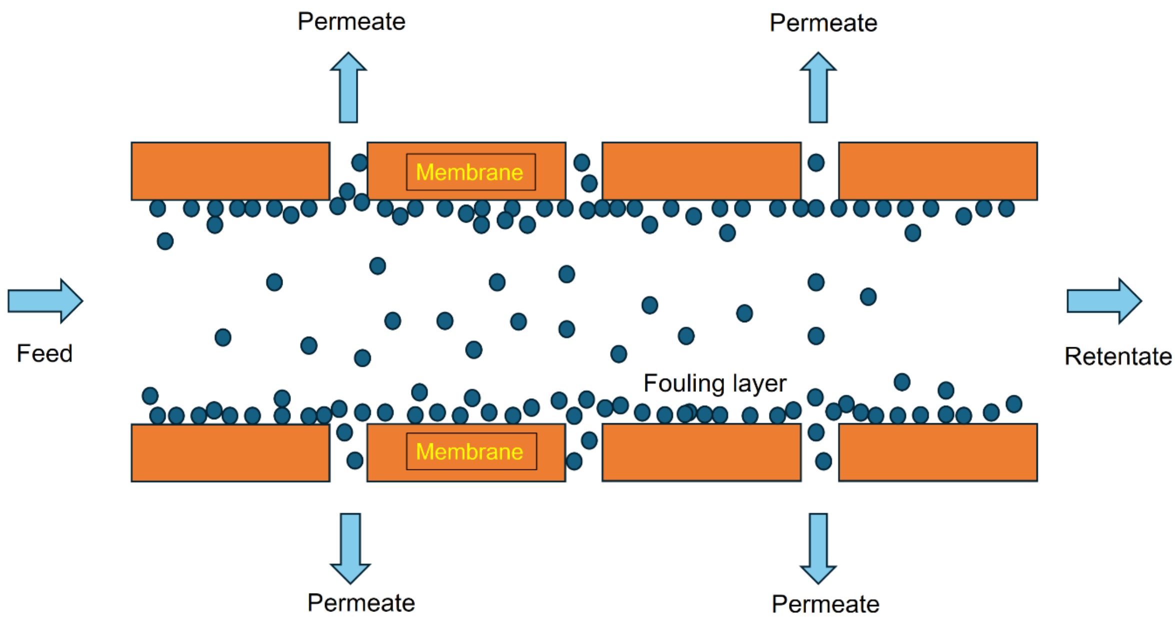


Figure 1: Cross-flow microfiltration process and Membrane fouling

2.2 Different membrane fouling mechanisms

Membrane fouling in microfiltration may be described by different mechanisms including standard blocking mechanism, complete blocking mechanism, intermediate blocking mechanism, and cake filtration mechanism [2]. The working of these mechanisms is depicted in Figure 2.

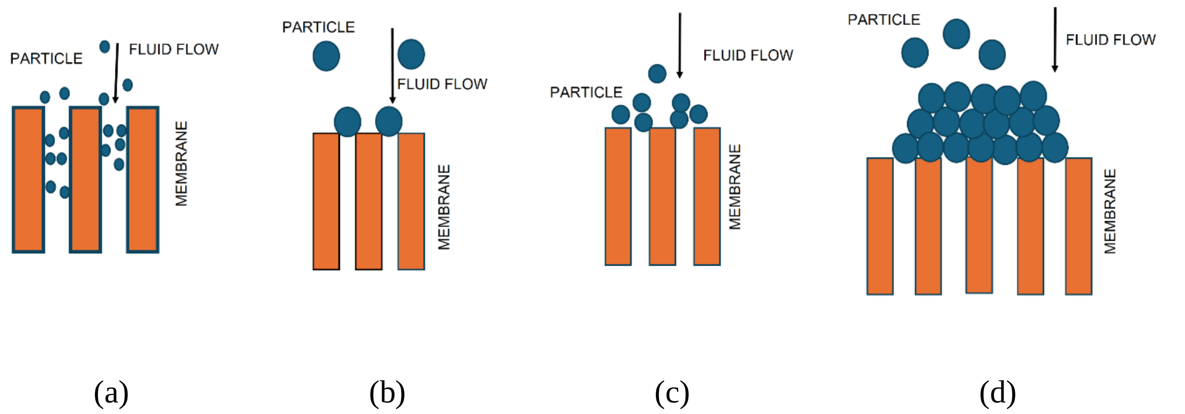


Figure 2: Membrane fouling mechanisms: (a) Standard blocking; (b) Complete blocking; (c) Intermediate blocking; (d) Cake filtration

In a standard blocking mechanism, the solute is adsorbed or deposited inside the membrane pores, which obstructs the flow of solvent across the membrane (Figure 2 (a). The deposition of these particles increases with time and membrane pores are completely blocked after some time. In the complete blocking stage, membrane pores are completely blocked by solute particles (Figure 2 (b)). On the other hand, in the intermediate blocking stage pores are partially blocked by solute particles (Figure 3 (c)) and deposited layer by layer on the membrane surface. Later a thick layer of the foulant is deposited on the membrane surface leading to a reduction of hydraulic and solute permeability [20, 21]. This mechanism is called the cack filtration mechanism (Figure 4 (d)). In constant trans-membrane pressure operations, Eq. (1 – 4) represents standard blocking, complete blocking, intermediate, and cake filtration mechanisms respectively.

$$\frac{J}{J_o} = (1 + kt)^{-2} \tag{1}$$

$$\frac{J}{J_o} = ln(-kt) \tag{2}$$

$$\frac{J}{J_o} = (1 + kt)^{-1} \tag{3}$$

$$\frac{J}{J_o} = (1 + kt)^{-0.5} \tag{4}$$

Where J_o (m/s or L/m^{2}h) is the initial cross membrane flux; J (m/s or L/m^{2}h) is the flux after time t (s), and k (s^{-1}) is a constant.

In several cases, the fouling mechanism may be a combination of more than one of these phenomena [20, 21]. Moreover, these models do not incorporate the effects of different operating parameters such as trans-membrane pressure, feed flow rate, feed temperature, etc, which are required to design and operate commercial-scale operations.

2.3 ANN-based MODELING

The Artificial Neural Network-based approach is a machine learning tool, that mimics the working of the human mind. It reorganizes the inherent correlations between input and output parameters based on the experience of the available dataset [23]. Thus, it is an empirical MODELING technique and works for complex non-linear problems, where the physics behind the process is not well known or difficult to solve [23]. An ANN algorithm contains three layers i.e., the input layer, hidden layer, and output layer. These layers are connected to each other by neurons. These neurons process the available dataset and extract useful information, which correlates with the input and output parameters. Details of the ANN functions used in this study may be found in [22, 23].

CHAPTER-3

PROCEDURE

In this study, experimental data from two published studies were used to train, validate, and test the ANN [11, 17]. In [11], a PES flat sheet membrane of nominal pore size 0.45 µm was used to separate whey proteins from the model whey solution. Similarly, in [17], a PES flat sheet membrane with a nominal pore size of 0.1 µm was used to separate whey protein β-lactoglobulin from the model whey solution. 224 experimental data points of [11] were used to train ANN to study the effects of trans-membrane pressure and Reynolds number of feed streams. On the other hand, 51 experimental data points [17] were used to train the ANN to study the effects of feed temperature. The range of different input and output parameters is given in Table 1. Details of the experimental data points are reported in Appendix 1.

Reference	Parameter	Range
[11]	Operation Time	0 – 2500 s
	Trans-membrane pressure	0.5 – 2 bar
	Reynolds number of feed solution	750 – 2500
	Flux	0 – 55 L/h.m^2
[17]	Operation Time	0 – 170 s
	Feed temperature	30 – 40 ^oC
	Flux	0 - 22 × 10^{-5} m/s

Table 1: Range of different parameters

In this study, the Levemberg- Marquardt Algorithm in the Feed Forward Approach [22, 23] was used as an ANN algorithm coded in MATLAB Deep Learning Toolbox. It consists of a single hidden layer containing several neurons. Initially, several neurons in the hidden layer were optimized to minimize the mean squared error between experimental results and model predictions used in all training validation and testing of the ANN. 70% of the data points were used to train the ANN. 15 % of data points were used to train the ANN and 15 % of data points were used to test the ANN. Trained was used for Artificial Neural Networking. Since, the experimental results from both studies [11, 17] were performed with different membranes and feed systems, ANN was trained separately for both studies. Levenberg-Marquardt Algorithm in the Feed-forward approach was used in simulations. A single hidden layer containing the number of neurons is applied in ANN. Initially, simulations were conducted to determine the optimum neurons in the hidden layer to minimize the MSE between experimental results and model predictions. Trained ANN with the optimum number of the ANN was then used to simulate the effects of different operating parameters. Simulations were conducted by varying a single operating parameter along with time to understand the reduction in flux representing the fouling in the membrane.

Value of k in Eqs. (1 – 4) is a constant, depending on the operating variables. Thus, the value of k was determined for each model as well as for each set of operating parameters by fitting the experimental results in Eqs. (1 – 4). An objective function shown in Eq. (5) was defined as the function of k.

$$f(k) = \sum_{i=1}^{N} abs\left(1 - \frac{J_{i,exp}}{J_{i,the}}\right) \tag{5}$$

Where, $J_{i,exp}$ is the experimental flux at i^{th} data point, $J_{i,the}$ is the theoretical flux at i^{th} data point, N is the total number of data points, and $f(k)$ is the objective function. This function is minimized by using the nonlinear simplex optimization method. The value of k where the objective function is minimized, is considered the true value of k, which is then used to determine the value of theoretical flux at different data points. This parameter estimation method along with simulation was coded in MATLAB and the MATLAB optimization toolbox was used to run the nonlinear simplex optimization method.

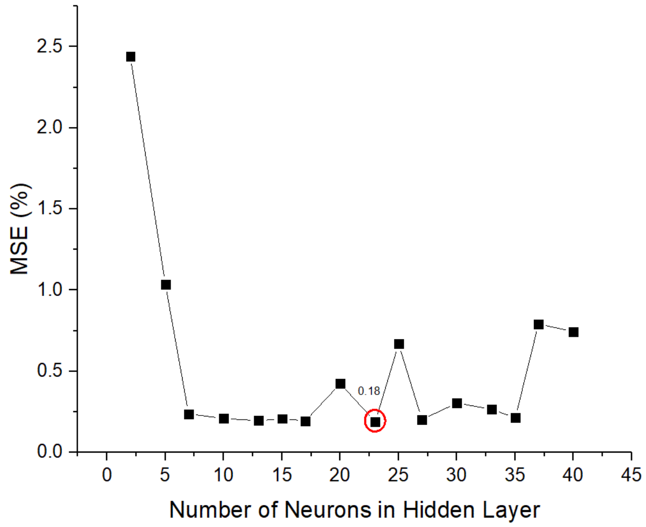
CHAPTER-4

RESULTS AND DISCUSSION

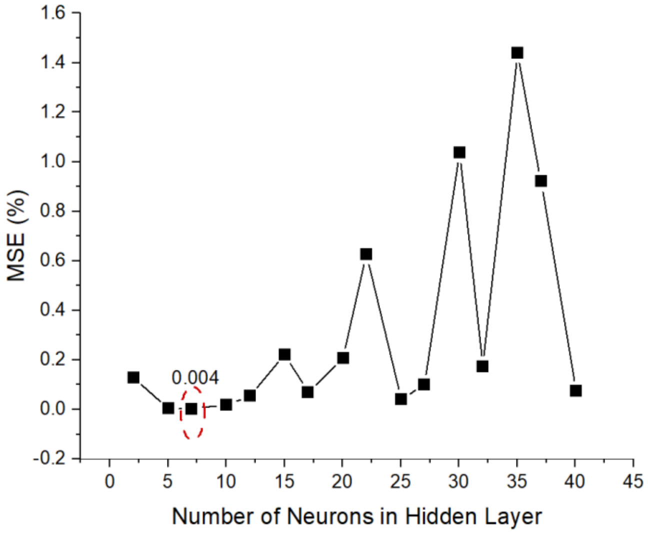
4.1 ANN Training and Validation

ANN was trained separately for the experimental results extracted from the articles [11] and [17]. Experimental results from the first article [11] were used to study the effects of trans-membrane pressure and Reynolds number. Similarly, experimental results from the second article were used to study the effects of feed temperature. Details of the experimental data points extracted from both articles are reported in Appendix 1 and 2.

Figure 3 shows values of mean squared error (MSE) with respect to the number of neurons in the hidden layer. Results show that for trans-membrane pressure and Reynolds number, minimum MSE (0.18) was obtained with 23 neurons in the hidden layer (Figure 3 (a)). On the other hand, for feed temperature minimum MSE (0.004) was obtained with 7 neurons in the hidden layer (Figure 3 (b)). Simulations showed that a lesser number of neurons are required to train ANN in case of feed temperature than trans-membrane pressure and Reynolds number. Moreover, the value of minimum MSE achieved for feed temperature (0.004) was also significantly lower than trans-membrane pressure and Reynolds number. This may be due to the higher number of input parameters i.e., 2 in the case of the first study (Figure 3 (a)) than the second study (Figure 3 (b)). Additionally, experiments were performed for longer periods of time (0 – 2500 s) in the first study than in the second study (0 – 170 s), which may also affect the number of neurons required to train the ANN. Trained ANNs with minimum MSE (23 in the first study and 7 in the second study were used for further simulations and analysis.



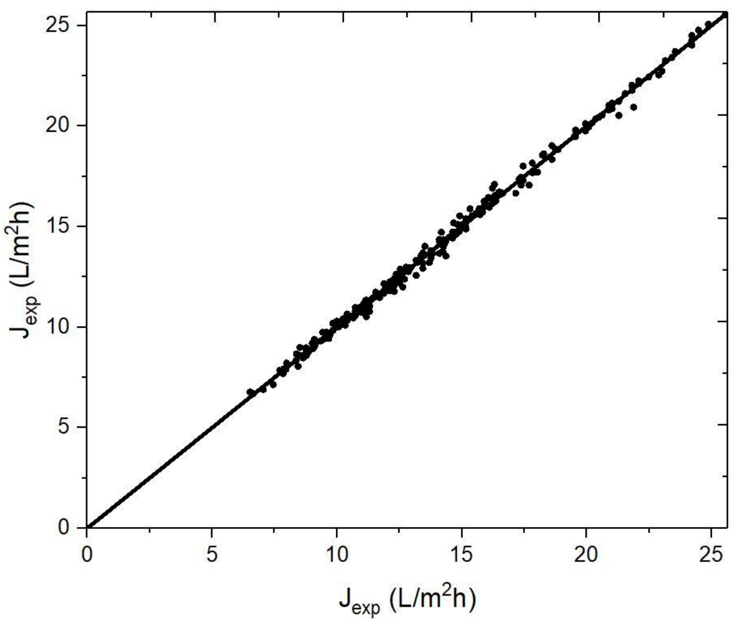
(a)



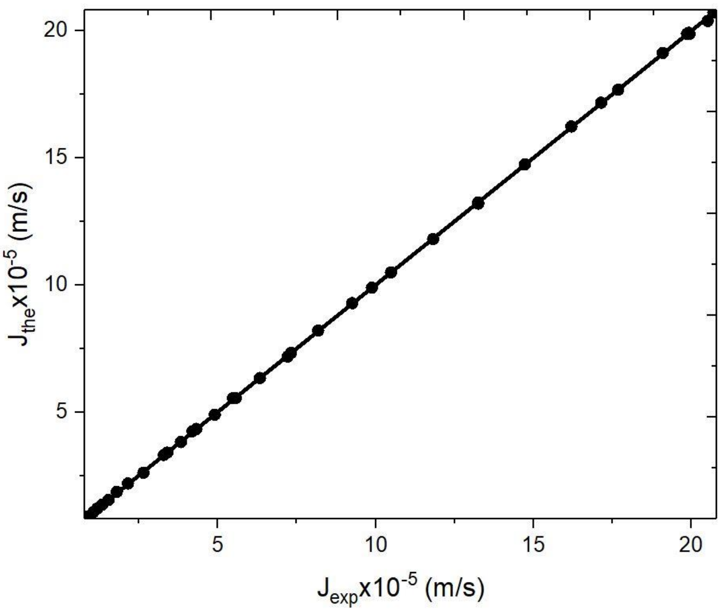
(b)

Figure. 3: Optimization of the number of neurons in the hidden layer: (a) ANN trained for trans-membrane pressure and Reynolds number; (b) ANN trained for feed temperature

Figure 4 compares the experimental results and ANN predictions on all experimental data points. Simulations showed that ANN predictions were well-fitted with experimental results for both studies. The value of the coefficient of determination (R^2) was calculated at 0.9954 for the first study and 0.9999 for the second study, which validates the train ANN and proves the correctness of the ANN predictions at different operating conditions. Now, after validation, trained ANNs can be used to analyze the effects of operating parameters on membrane fouling during whey processing.



(a)



(b)

Figure. 4: Regression study, comparison of experimental results and model predictions: (a) ANN trained for trans-membrane pressure and Reynolds number; (b) ANN trained for feed temperature

4.2 Effects of operating parameters on membrane fouling

4.2.1 Effects of trans-membrane pressure

Figure: 5 shows the effects of trans-membrane pressure on the membrane flux with varying operational time. Trans-membrane pressure varied from 0.5 to 2 bar for 0 – 2500 s operation. Results showed that the initial value of flux increased with increasing trans-membrane pressure which acts as the driving force. However, after 1000 s of operations this trend was reversed and lower flux was observed at high pressure. These results indicate that the initial value of fluxes is higher at high trans-membrane pressure. However, higher pressure also causes high fouling as it pushes more solute particles towards the membrane surface. Thus, the value of flux reduces significantly at higher pressure after some time. On the other hand, a lesser reduction in flux was observed at lower pressure due to lower fouling. In simulations, 36.3 % flux reduction was observed at 0.5 bar pressure in a 2500 s run. While 76.39 % of flux reduction was observed at 2 bar pressures in a 2500 s run. These results suggest that the microfiltration system should operate at lower pressure to minimize the fouling and increase the operational time before the cleaning cycle.

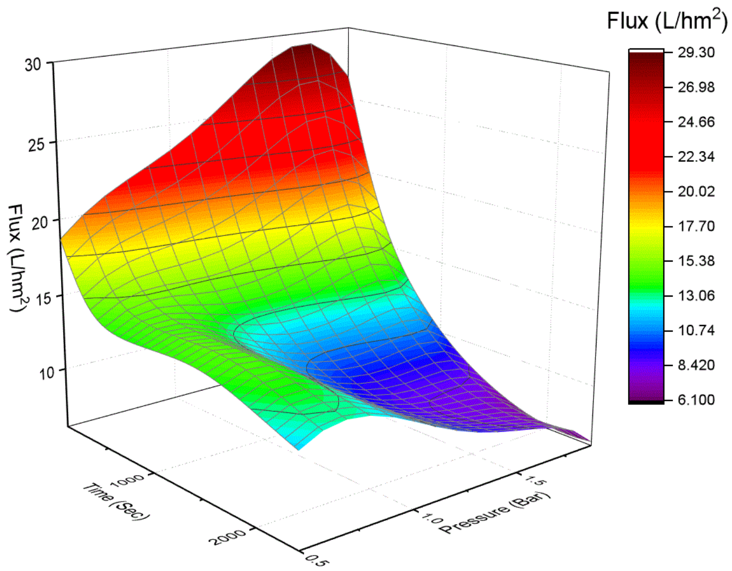


Figure. 5: Effects of transmembrane pressure on flux

4.2.2 Effects of Reynolds number

Figure 6 shows the effects of the Reynolds number of the flux with varying operational time. These simulations were performed with varying Reynolds numbers from 500 to 2500 for 2500 s of operation. Results showed that the value of flux reduced drastically with time at a lower Reynolds number due to the membrane fouling. However, the fouling effect became less dominant with increasing Reynolds number, as higher Reynolds number promoted mixing and turbulence. 70.53 % of flux reduction was observed after 2500 s of operation at 750 Reynolds number. While 50.57 % of flux reduction was observed in the same duration at 2500 Reynolds number. Turbulence in the feed stream prevents the solute particles from agglomerating at the membrane surface hence reducing the fouling. These results suggest that the microfiltration process should run at Reynolds number to promote turbulence in the feed section. This may be achieved by running the microfiltration at higher flow rates by reducing the diameter of the feed channel or by reducing the viscosity or density of the feed.

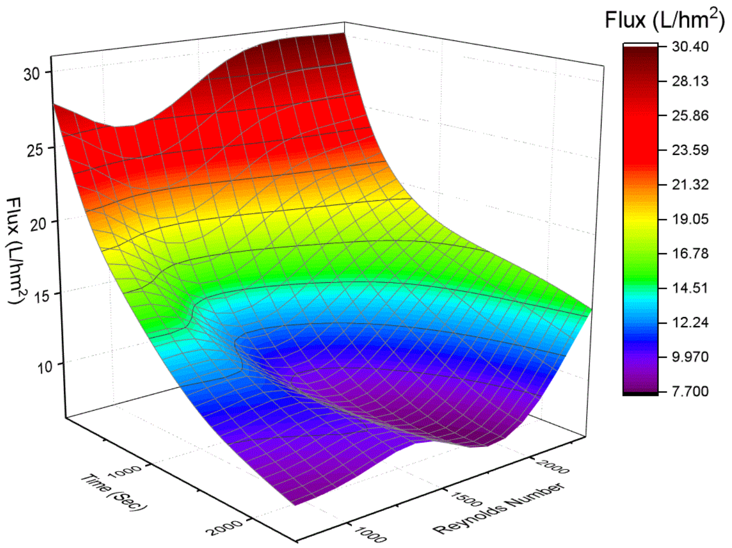


Figure. 6: Effects of Reynolds number on flux

4.2.3 Effects of Feed Temperature

Figure 7 shows the effects of feed temperature on the flux with varying operational time. Results showed that initially at t=0, flux increased with increasing feed temperature from 30 ^oC to 40 ^oC. Higher feed temperature increases diffusive and convective mass transport due to an increase in diffusivity coefficients and reduction of viscosity and density of the fluid, which altimetry increases the flux at the initial stage of operation. However, higher fluid flux also forces more solute particles on the surface of the membrane, which quickly start to agglomerate at the surface of the membrane, and thus, the membrane fouls very rapidly and causes the rapid reduction of flux at higher temperatures. Therefore, a drastic reduction of flux was observed at higher temperatures. At 30 ^{o}C, a 10.01 % flux reduction was observed after 170 s of operations. On the other hand, 87.38 % flux reduction was observed at 40 ^{o}C with the same duration of operation. These results suggest that the microfiltration process should operate at lower temperatures to reduce the effects of membrane fouling and increase the operational time.

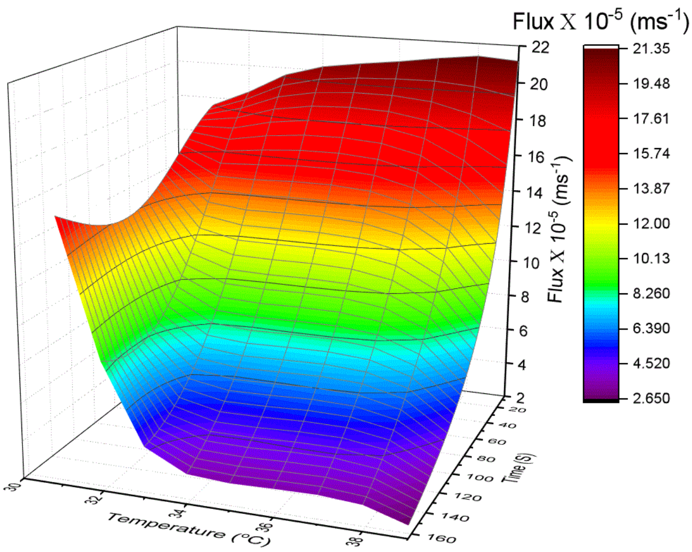


Figure. 7: Effects of feed temperature on flux

4.3 Comparison of the performance ANN with other mathematical models

Membrane fouling in microfiltration can also be modeled by using different theoretical models as reported in Eq. 1 to Eq. 4. Experimental results from [11] were fitted in these models by minimizing Eq. 5 as reported in Eq. 4. Comparison of experimental results with model predictions (including ANN) are reported in the Appendix 1 and 2

The average relative error between experimental readings and various fouling model predictions is reported in Table 2. Simulations showed that the ANN based model predictions are far more accurate than the all-different theoretical models. This proves that the ANN based approach is more accurate in predicting the fouling in the microfiltration process.

Among all theoretical models, the intermediate blocking model showed the least average relative error (0.185), which indicates that fouling occurred in the microfiltration membrane through the intermediate blocking mechanism.

Name of the Model	**Average relative error between experimental readings and model predictions**
Standard blocking	0.283
Complete blocking	0.365
Intermediate blocking	0.185
Cake filtration	0.303
ANN based model	0.0165

Table 2: Values of Average relative errors between experimental readings and model predictions for different models

CHAPTER-5

CONCLUSION

This study proves that an artificial neural network-based approach can be successfully applied to model the effects of operating parameters on membrane fouling in case of protein separation from milk whey. Furthermore, comparison with other theoretical models also confirms that ANN based technique provides much better predictions. A low to moderate number of neurons (7 to 23) in the hidden layer is enough to successfully train the ANN for the prediction of membrane fouling.

Simulations showed that the trans-membrane pressure, Reynolds number of the feed stream, and feed stream temperature all are the influencing operating parameters affecting the membrane fouling. Moreover, low to moderate trans-membrane pressure and high Reynolds number are preferred operating conditions to minimize the effects of membrane fouling. Higher trans-membrane pressure forces the solute particles on the surface of the membrane leading to more fouling. On the other hand, a high Reynolds number enhances the turbulence in the feed stream, which reduces the membrane fouling. Similarly, a lower feed temperature is the preferred operating condition to minimize the effects of fouling, as a higher feed temperature enhances the solvent flux which forces the solute particles toward the membrane surface due to convective effects.

Overall, this study proves that ANN based MODELING is a very useful tool to predict the effects of operating conditions in microfiltration in case of whey protein concentration. ANN can help to minimize the effects of membrane fouling by running the system at optimal conditions.

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APPENDICES

Appendices-1

Comparison of experimental results [11] and ANN predictions

Trans-membrane pressure (bar)	Reynolds number	Time (s)	Theoretical flux (L/m^2s)	Experimental flux (L/m^2s)	Relative error
1	750	200	15.96	16.14	-0.01
1	750	220	15.83	15.72	0.01
1	750	270	14.63	14.73	-0.01
1	750	290	14.10	14.36	-0.02
1	750	330	13.84	13.66	0.01
1	750	350	13.17	13.33	-0.01
1	750	380	12.77	12.87	-0.01
1	750	420	12.51	12.31	0.02
1	750	440	12.24	12.05	0.02
1	750	460	12.11	11.81	0.02
1	750	490	11.71	11.47	0.02
1	750	530	11.31	11.06	0.02
1	750	560	11.18	10.78	0.04
1	750	590	11.18	10.52	0.06
1	750	720	9.71	9.59	0.01
1	750	780	9.18	9.25	-0.01
1	750	830	8.51	8.99	-0.06
1	750	900	8.38	8.67	-0.04
1	750	950	8.65	8.47	0.02
1	750	1020	7.98	8.22	-0.03
1	750	1080	7.98	8.02	0.00
1	750	1140	7.72	7.84	-0.02
1	750	1200	7.85	7.69	0.02
1	750	1500	7.45	7.14	0.04
1	750	1800	7.05	6.90	0.02

1	750	2100	6.52	6.77	-0.04
1	750	2400	6.65	6.69	-0.01
1	1250	200	17.69	17.07	0.04
1	1250	220	17.16	16.66	0.03
1	1250	240	16.36	16.26	0.01
1	1250	260	15.70	15.89	-0.01
1	1250	290	15.30	15.36	0.00
1	1250	320	15.17	14.87	0.02
1	1250	350	14.63	14.43	0.01
1	1250	400	14.24	13.77	0.03
1	1250	420	14.37	13.54	0.06
1	1250	450	13.70	13.21	0.04
1	1250	480	13.44	12.92	0.04
1	1250	520	13.17	12.57	0.05
1	1250	570	12.51	12.19	0.03
1	1250	600	12.64	11.99	0.05
1	1250	650	11.57	11.70	-0.01
1	1250	720	11.18	11.35	-0.02
1	1250	780	11.18	11.11	0.01
1	1250	840	11.18	10.89	0.03
1	1250	900	11.04	10.71	0.03
1	1250	950	10.64	10.58	0.01
1	1250	1020	10.38	10.42	0.00
1	1250	1080	10.38	10.29	0.01
1	1250	1120	10.11	10.22	-0.01
1	1250	1200	9.98	10.09	-0.01
1	1250	1500	9.58	9.75	-0.02
1	1250	1800	9.45	9.39	0.01
1	1250	2100	9.05	8.93	0.01
1	1250	2400	8.78	8.59	0.02
1	1750	200	21.29	20.53	0.04

1	1750	220	20.22	20.16	0.00
1	1750	240	19.56	19.80	-0.01
1	1750	260	19.56	19.46	0.00
1	1750	300	18.76	18.84	0.00
1	1750	320	18.23	18.56	-0.02
1	1750	350	17.83	18.16	-0.02
1	1750	390	17.83	17.68	0.01
1	1750	420	17.29	17.36	0.00
1	1750	490	16.50	16.73	-0.01
1	1750	510	16.36	16.57	-0.01
1	1750	540	16.23	16.35	-0.01
1	1750	570	16.23	16.15	0.00
1	1750	600	16.10	15.97	0.01
1	1750	660	15.57	15.65	-0.01
1	1750	720	15.17	15.38	-0.01
1	1750	790	15.03	15.11	-0.01
1	1750	840	15.17	14.94	0.01
1	1750	900	14.90	14.77	0.01
1	1750	960	14.77	14.61	0.01
1	1750	1020	14.50	14.47	0.00
1	1750	1080	14.37	14.35	0.00
1	1750	1140	14.24	14.24	0.00
1	1750	1200	14.24	14.14	0.01
1	1750	1500	13.44	13.69	-0.02
1	1750	1800	13.30	13.26	0.00
1	1750	2100	12.77	12.98	-0.02
1	1750	2400	12.90	12.87	0.00
1	2500	190	25.54	25.52	0.00
1	2500	220	24.88	25.06	-0.01
1	2500	240	24.48	24.77	-0.01
1	2500	260	24.21	24.50	-0.01

1	2500	280	24.21	24.25	0.00
1	2500	300	24.21	24.02	0.01
1	2500	330	23.55	23.70	-0.01
1	2500	360	23.41	23.41	0.00
1	2500	380	23.15	23.24	0.00
1	2500	450	23.02	22.73	0.01
1	2500	480	22.88	22.54	0.01
1	2500	500	22.48	22.43	0.00
1	2500	540	22.08	22.24	-0.01
1	2500	570	22.08	22.10	0.00
1	2500	590	21.82	22.02	-0.01
1	2500	660	21.82	21.78	0.00
1	2500	720	21.55	21.62	0.00
1	2500	900	21.29	21.23	0.00
1	2500	950	21.02	21.15	-0.01
1	2500	1020	20.89	21.03	-0.01
1	2500	1080	20.89	20.94	0.00
1	2500	1140	21.02	20.87	0.01
1	2500	1200	20.89	20.79	0.00
1	2500	1500	20.62	20.54	0.00
1	2500	1800	20.35	20.35	0.00
1	2500	2100	19.96	20.12	-0.01
1	2500	2400	19.96	19.75	0.01
0.5	1250	200	12.54	12.88	-0.03
0.5	1250	220	12.38	12.63	-0.02
0.5	1250	240	12.62	12.39	0.02
0.5	1250	260	11.89	12.16	-0.02
0.5	1250	300	11.56	11.74	-0.02
0.5	1250	360	11.15	11.21	-0.01
0.5	1250	390	10.90	10.98	-0.01
0.5	1250	420	11.31	10.79	0.05

0.5	1250	480	10.66	10.46	0.02
0.5	1250	510	10.41	10.32	0.01
0.5	1250	540	10.16	10.20	0.00
0.5	1250	570	10.33	10.10	0.02
0.5	1250	590	10.00	10.03	0.00
0.5	1250	660	9.84	9.83	0.00
0.5	1250	720	9.67	9.69	0.00
0.5	1250	780	9.67	9.56	0.01
0.5	1250	900	9.34	9.31	0.00
0.5	1250	960	9.02	9.20	-0.02
0.5	1250	1020	9.10	9.08	0.00
0.5	1250	1080	8.77	8.97	-0.02
0.5	1250	1140	8.77	8.86	-0.01
0.5	1250	1200	8.85	8.76	0.01
0.5	1250	1500	8.36	8.34	0.00
0.5	1250	1800	8.44	8.05	0.05
0.5	1250	2100	7.95	7.90	0.01
0.5	1250	2400	7.87	7.92	-0.01
1	1250	200	17.38	17.07	0.02
1	1250	220	16.64	16.66	0.00
1	1250	240	15.90	16.26	-0.02
1	1250	260	15.33	15.89	-0.04
1	1250	280	14.92	15.53	-0.04
1	1250	300	14.67	15.19	-0.04
1	1250	330	14.18	14.72	-0.04
1	1250	360	14.10	14.29	-0.01
1	1250	380	13.52	14.02	-0.04
1	1250	420	13.36	13.54	-0.01
1	1250	450	13.20	13.21	0.00
1	1250	480	12.79	12.92	-0.01
1	1250	500	12.54	12.74	-0.02

1	1250	540	12.30	12.41	-0.01
1	1250	560	12.13	12.26	-0.01
1	1250	600	11.97	11.99	0.00
1	1250	660	11.64	11.64	0.00
1	1250	710	11.39	11.40	0.00
1	1250	780	11.07	11.11	0.00
1	1250	840	11.15	10.89	0.02
1	1250	900	10.82	10.71	0.01
1	1250	950	10.49	10.58	-0.01
1	1250	1020	10.25	10.42	-0.02
1	1250	1080	10.00	10.29	-0.03
1	1250	1140	9.84	10.19	-0.04
1	1250	1200	10.08	10.09	0.00
1	1250	1500	9.43	9.75	-0.03
1	1250	1800	9.10	9.39	-0.03
1	1250	2100	8.77	8.93	-0.02
1	1250	2400	8.52	8.59	-0.01
1.5	1250	200	21.89	20.94	0.04
1.5	1250	220	20.49	20.44	0.00
1.5	1250	240	20.08	19.95	0.01
1.5	1250	260	19.51	19.49	0.00
1.5	1250	290	18.85	18.82	0.00
1.5	1250	300	18.28	18.61	-0.02
1.5	1250	330	17.46	18.01	-0.03
1.5	1250	360	17.38	17.45	0.00
1.5	1250	380	16.31	17.10	-0.05
1.5	1250	420	16.07	16.45	-0.02
1.5	1250	450	15.90	16.00	-0.01
1.5	1250	480	15.74	15.59	0.01
1.5	1250	510	15.16	15.21	0.00
1.5	1250	600	14.34	14.22	0.01

1.5	1250	660	14.10	13.67	0.03
1.5	1250	720	13.44	13.19	0.02
1.5	1250	780	12.87	12.76	0.01
1.5	1250	840	12.70	12.39	0.02
1.5	1250	900	12.30	12.06	0.02
1.5	1250	960	12.30	11.77	0.04
1.5	1250	1020	11.64	11.53	0.01
1.5	1250	1080	11.15	11.31	-0.01
1.5	1250	1140	11.07	11.13	-0.01
1.5	1250	1200	10.74	10.98	-0.02
1.5	1250	1500	10.74	10.59	0.01
1.5	1250	1800	10.33	10.40	-0.01
1.5	1250	2100	10.08	10.02	0.01
1.5	1250	2400	9.67	9.44	0.02
2	1250	180	18.61	19.02	-0.02
2	1250	210	18.61	18.34	0.01
2	1250	240	18.03	17.70	0.02
2	1250	260	17.46	17.29	0.01
2	1250	280	16.23	16.90	-0.04
2	1250	300	16.31	16.53	-0.01
2	1250	330	15.98	16.02	0.00
2	1250	360	15.41	15.54	-0.01
2	1250	390	14.84	15.10	-0.02
2	1250	420	14.75	14.70	0.00
2	1250	450	14.26	14.34	-0.01
2	1250	480	14.26	14.01	0.02
2	1250	500	13.77	13.81	0.00
2	1250	540	13.77	13.44	0.02
2	1250	570	13.44	13.19	0.02
2	1250	600	12.95	12.96	0.00
2	1250	660	12.46	12.57	-0.01

2	1250	720	12.38	12.23	0.01
2	1250	775	12.05	11.96	0.01
2	1250	840	11.89	11.69	0.02
2	1250	900	11.48	11.46	0.00
2	1250	960	11.31	11.27	0.00
2	1250	1020	11.15	11.09	0.01
2	1250	1080	10.82	10.93	-0.01
2	1250	1140	10.74	10.78	0.00
2	1250	1200	10.41	10.64	-0.02
2	1250	1500	10.08	10.16	-0.01
2	1250	1800	9.84	9.84	0.00
2	1250	2100	9.59	9.48	0.01
2	1250	2400	9.10	9.06	0.00

Appendix-2

Comparison of experimental results [17] and ANN predictions

Temperature (^oC)	Time (s)	Theoretical flux (L/m^2s)	Experimental flux (L/m^2s)	Relative error
30	4.92	19.87	19.86	0.03
30	15.00	19.87	19.87	-0.03
30	24.85	19.87	19.88	-0.03
30	34.93	19.87	19.87	-0.02
30	45.01	19.87	19.87	0.00
30	54.86	19.87	19.87	0.00
30	64.94	19.87	19.87	-0.01
30	75.02	19.87	19.87	-0.02
30	84.86	19.87	19.87	-0.02
30	94.95	19.87	19.87	-0.02
30	104.79	19.87	19.87	-0.01
30	114.87	19.87	19.87	-0.01
30	124.95	19.87	19.88	-0.03
30	135.03	19.87	19.88	-0.07
30	144.88	19.87	19.90	-0.13
30	154.96	19.92	19.91	0.01
30	164.81	19.87	19.94	-0.34
35	4.92	20.38	20.51	-0.63
35	15.00	19.12	19.09	0.16
35	24.85	17.68	17.68	-0.03
35	34.93	16.23	16.20	0.19
35	44.78	14.74	14.73	0.04
35	54.86	13.25	13.25	-0.02
35	64.94	11.80	11.82	-0.20
35	75.02	10.49	10.49	0.05
35	85.10	9.28	9.27	0.18
35	94.95	8.21	8.19	0.28
35	104.79	7.18	7.22	-0.52
35	114.87	6.34	6.34	0.00
35	124.95	5.55	5.57	-0.40
35	134.80	4.90	4.91	-0.35
35	144.88	4.34	4.33	0.20
35	154.73	3.82	3.84	-0.34
35	164.81	3.40	3.41	-0.16
40	4.92	20.71	20.70	0.06
40	15.00	17.16	17.14	0.12
40	25.08	13.20	13.25	-0.40
40	34.93	9.89	9.88	0.03
40	44.78	7.32	7.33	-0.06
40	54.86	5.55	5.49	1.15

40	64.94	4.24	4.21	0.88
40	75.02	3.31	3.30	0.43
40	84.86	2.61	2.65	-1.48
40	94.95	2.19	2.16	1.31
40	104.79	1.87	1.81	2.83
40	114.87	1.54	1.55	-0.50
40	124.95	1.35	1.35	0.38
40	134.80	1.21	1.20	1.31
40	144.88	1.07	1.07	0.00
40	154.96	0.93	0.97	-3.94
40	164.81	0.89	0.88	0.21

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LIST OF PUBLICATIONS AND THEIR PROOFS

1.Poster presented in IDEAS 2024 Conference in New York University Abu Dhabi Campus.

NYU ABU DHABI
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RESEARCH
CENTER

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NYU ABU DHABI

The New York University Water Research Center (NYUAD-WRC) is pleased to certify that

Prafful Kumar Meena

Participated in the International Desalination Environment and Sustainability (IDEAS) Conference 2024 with a Poster Presentation titled *"Artificial neural network based modelling of temperature dependent membrane fouling in ultrafiltration process"*

January 22-23 2024

N. Hilal

Nidal Hilal, DSc, PhD, Euro Ing, CEng,
FIChemE, FLSW, FRSC
Chairman of IDEAS 2024
Professor of Engineering
Director | NYUAD Water Research Center

2.Poster presented in CARBOXXXVII 2023 in DTU college.

CARBOXXXVII

International Conference on Basic, Analytical and Allied Sciences at the Interface of Carbohydrates and Biomass Valorisation

30th November – 2nd December 2023

Certificate of Participation

This is to certify that Prof. / Dr. / Mr. / Ms. PRAFFUL KUMAR MEENA of DELHI TECHNOLOGICAL UNIVERSITY has attended this conference organized by Department of Applied Chemistry, Delhi Technological University, Delhi – 110042, India in association with Association of Carbohydrate Chemists and Technologists (India) & Indian Society of Analytical Scientists-Delhi Chapter at Delhi Technological University. He / She has participated as Invited Speaker / Session Chair / Organizer / Oral Paper Presenter / Poster Paper Presenter / Delegate / Sponsor in this CARBOXXXVII.

Prof. Anil Kumar	**Prof. Ram Singh**	**Prof. Vinod K. Tiwari**
Chairman	Convener cum Organizing Secretary	Hony. Secretary ACCTI

3. Journal Paper "Recovery of whey protein by using microfiltration: Artificial Neural Network based modeling and effects of different operating parameters" in review in Journal of Food Process Engineering (Manuscript No: JFPE-2024-Jun-0603) (Publisher: Wiley; Indexing: SCIE, Scopus)

Journal of Food Process Engineering

Journal of
Food Process Engineering

Recovery of whey protein by using microfiltration: Artificial Neural Network based modeling and effects of different operating parameters

Journal:	*Journal of Food Process Engineering*
Manuscript ID	JFPE-2024-Jun-0603
Wiley - Manuscript type:	Original Article
Date Submitted by the Author:	04-Jun-2024
Complete List of Authors:	Meena, Prafful meena; Delhi Technological University Department of Biotechnology Sharma, Jai Gopal; Delhi Technological University Department of Biotechnology Jain, Manish; Delhi Technological University Department of Applied Chemistry
Keywords:	Whey protein recovery, Whey processing, Microfiltration, Artificial neural network-based modeling

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PROFILE

* A proactive MSc Biotechnology student at Delhi Technological University.
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HELPER

Help in gathering food and clothes for the needy people.
I felt the pain of the people and it inspired me to work hard in my life.

ACHIEVEMENTS

Position of PG Representative in CULTURE COUNCIL (DTU COLLEGE SOCIETY)
Qualified for the second level in Science Olympiad Exam.

ADDITIONAL SKILLS

Team work - Believes in team work

Skill: Active listening , Interpersonal communication , Management

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Science related things - Always interested in science related knowledge .

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:-Attended a Conference in Delhi Technological University.