Porosity Prediction of Hollow Fiber Membrane Incorporating Neural Network and Digital Image Processing

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Abstract: The porosity of Hollow Fiber Membrane (HFM) is one of the main factors to evaluate the membrane performance in a special application. The study aims to introduce a novel and convenient method to calculate the overall porosity of the membrane. The artificial neural network (ANN) with a radial basis function (RBF) scheme was used to analyze the qualitative information of the outer surface of HFM based on the results obtained through a Field Emission Scanning Electron Microscope (FESEM) images. An image processing computer program was then developed to measure the HFM surface porosity from the FESEM images. The calculated overall porosity of the HFM was compared with the mathematical model. It was found that there is no significant difference in terms of results for both methods, thereby confirming the applicability of ANN for assessing the membrane porosity. This work presents a useful framework to evaluate the overall porosity of HFM considering different dope compositions and spinning conditions.

Key-Words: Hollow fiber membrane, Image processing, Artificial neural network, Overall porosity

1 Introduction

A porosity prediction of the porous HFMs seems crucial before applying the membranes in real application. It helps membranologists to detect an optimum solution composition and spinning condition based on the requirements of a specific membrane application in a minimum time.The prediction involves the examination of the surface and cross-section characteristics of the membranes. The overall porosity of the HFM can be obtained by several methods including molecular weight cut-off (MWCF) [1], pressure of bubbles [2], mercury intrusion [3], liquid–liquid or liquid-gas displacement [4] approaches. Recently, digital image processing (DIP) as a strong tool was also applied to determine the porosity of the membrane. The method uses FESEM images to detect the surface pores and then predict the overall porosity of membrane. However, since the membrane surface pores are not exactly cylindrical and straight, the predicted porosity may not be accurate. Therefore, an approach is proposed by training artificial neural network (ANN) which is expected able to predict the overall porosity of the HFMs better without considering the shape of the pores. The ANN offers the advantage of being easy to use and reduces the computing time of the membrane process simulation [5]. A type of ANN based on Radial Basis Function (RBF) was also employed for modeling the membrane process as described in [6]. However, the implementation of the ANN methods in this area of research is relatively in its infancy stage and still under development. Besides, the works did not consider aspects of determining the porosity of membrane which is regarded as a crucial factor to measure the mass transfer rate in porous membranes. Therefore, this work attempts to predict the membrane porosity using ANN and image processing techniques. The RBF network with three layers (input, hidden and output) using *Levenberg-Marquardt* (LM) algorithm was used to predict the overall porosity of the fabricated HFMs. The model was trained by the obtained porosity of membranes differing in dope compositions and spinning conditions.

2 Experimentation

Since the HFM fabrication and characterization are difficult and time consuming, only 57 samples were used for training and experimentation.

2.1 Membrane preparation

Commercial *Polysulfone* (PSf) polymer pellets (1700) were purchased from Arkema Inc., PA, USA. *1-Methyl-2pyrrolidone* (NMP) and *Polyvinyl-pyrrolidone K90* (PVP) were used as solvent and non-solvent additives in the polymer solution, respectively. The materials were dried in a vacuum oven for 48 hours at 60 ± 2 ^{o}C to remove the moisture content. PVP with content of 2.5 wt% of polymer was added in the solvent (NMP) for 1 hour under vigorous stirring. PSf polymer indifferent concentration (12% - 18%) was then gradually added to the mixture. The solutions were loaded into storage tank and pressured nitrogen of 1 bar forced the polymer solution to flow into the spinneret plant.

Water was utilized as the bore fluid liquid and loaded into the spinneret via the syringe pump. The HFMs were fabricated at ambient temperature of about 22 - 25 ^{o}C. Polymer concentration, dope extrusion and bore fluid flow rates were assumed as variables in our analysis. Water was used as the external coagulant bath and the temperature was kept constant during spinning. The detailed HFM fabrication via wet spinning method is described elsewhere [7]. The fabricated HFMs were immersed in water for 72 hours to remove the rest of NMP and PVP inside the spun HFMs. Table 2 lists specific detailed of the spinning procedure.

Table 2:HFM compositions and spinning conditions

Composition			Parameter	
PSf (gr)	PVP (gr)	NMP (gr)	DER (cm^3/min)	BFR (cm^3/min)
12.00	1.67	86.33	2.00	0.66
12.00	1.67	86.33	2.50	0.83
12.00	1.67	86.33	3.00	1
12.00	1.67	86.33	3.50	1.16
12.00	1.67	86.33	4.00	1.33
12.00	1.67	86.33	4.50	1.5
12.00	1.67	86.33	5.00	1.66
12.00	1.67	86.33	5.50	1.83
12.00	1.67	86.33	6.00	2

DER: Dope extrusion rate; BFR: Bore fluid flow rate

The composition of polymer was varied according to 14, 16,18,20 and 22 wt% with the same values for other variables in the next experiments.

2.2 Overall porosity

The porosity of the membrane has been defined as the ratio of the pores volume to the total volume of the membrane [8, 9]. The basic porosity equation of the HFM can be calculated using the following expression:

$$\varepsilon_m = \frac{\Delta \mathrm{m}}{\rho.\mathrm{x}\,\Delta \mathrm{V}} \quad (1)$$

Hence, the overall porosity of a membrane can be obtained as follows:

$$\varepsilon_m = \frac{\rho_w(\omega_1 - \omega_2)}{\rho_{p(\omega_1 - \omega_2)} + \rho_\omega(\omega_2)} \quad (2)$$

Where, w_1 and w_2 are the weights of the wet and the dry membrane, respectively while ρ_w and ρ_p are density of the water and polymer solution, respectively. Based on the above equation, the porosity ε_m can be described as a non-dimensional parameter and in most literature, it is written as a percentage concentrate (%).

3 Field Emission Scanning Electron Microscopy (FESEM)

The membranes were put on holders and coated by sputtering platinum. A *Zeiss Supra 35VP* FESEM, was used to observe the outer surface of the fabricated membranes. For computing and processing, the FESEM images were used as the feed to the ANN in order to get an accurate overall porosity at the outer layer.

4 Artificial IntelligenceApproach

Generally, the grey images from the outer surface of a porous membrane are between zero and 255 pixels in which, the pixels with low and high luminance were assumed as pore areas and background, respectively.

In the first step, the FESEM images were resized into 1000×1000 square pixels in order for them to be transferred to the computer for analysis. For filtration, the *medfilt2* function was used to eliminate the noises from the colour images. Then *Unsharp* algorithm was used to increase the intensity of the images and edges. Before classification, the images were adjusted as red, green and blue (RGB) images to detect of the pore boundaries clearly. The surface porosity of the fabricated membranes was calculated using the following equation:

$$\varepsilon = \frac{\int_0^h (Ap)_z dz}{(At)} \quad (3)$$

Where *At* is the total area of image, *Ap* is the area porosity at distance *z* and *h* is the height of image.

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To obtain accurate results, three modules for each membrane type were prepared. The results were averaged and the mean surface porosity of three modules was assumed. The objective of a neural network is to compute the porosity values by some internal calculations on FESEM images of membranes in different dope composition, DER and BFR rates. Neurons (or cells) are processing elements that carry out simple computations from a vector of composition, DER and BFR rates. A neuron performs a non-linear transformation of the weighted sum of the incoming neuron inputs to produce the output ofthe neuron.

Results from the works done by Poggio and Girosi [10] and Antsaklis [11] revealed that the RBF network amongst all the feed-forward networks has the highest ability to predict the approximation properties of the membranes. In this work, the RBF network was used to predict the porosity of the membranes. The model was trained, taking into account the obtained porosity of membranes differing in dope compositions and spinning conditions. In terms of the data composition, 70% of them is assumed as the training data, 15% as the testing data while the the rest is assumed as validation data. The essential building block of the RBF neural network applied in this study is shown in Fig. 1.

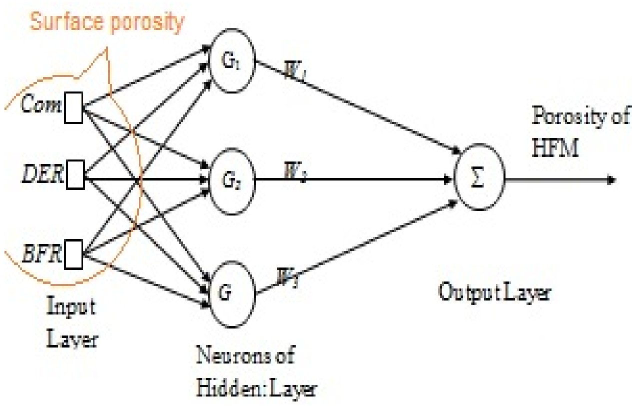


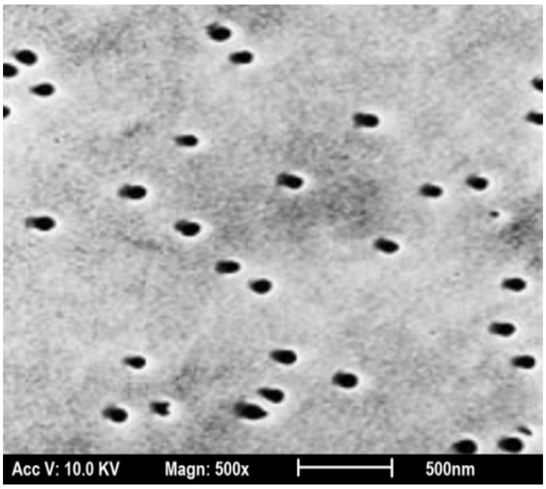
Fig. 1. Regularization RBF network with one hidden layer. *G* and *W* are the functions in hidden layer and weights, respectively.

4 Results and Discussion

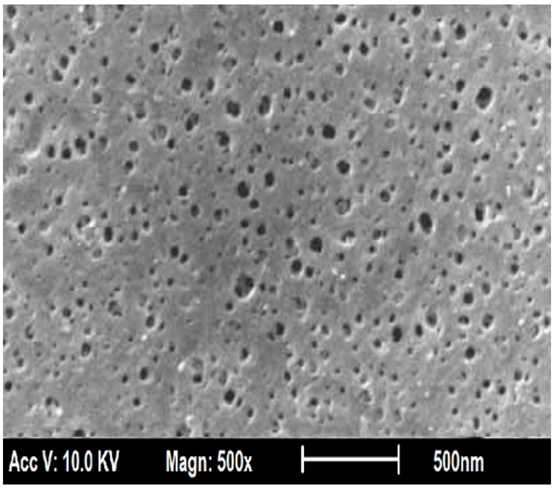
The results obtained from the study are presented, analyzed and discussed in the following sections.

4.1 FESEM and image analyses (pre-processing)

Figure 2 shows FESEM surface micrographs of fabricated membranes in different compositions and spinning conditions. As can be seen, the membranes of lower polymer concentration possess larger surface pore size and higher porosity as depicted in Figure 2 (b) compared to that of those with higher concentration as shown in Figure 2 (a).



(a)



(b)

Fig.2. FESEM image of the outer surface of the PSF HFMs: (a) low porosity HFM: PSf12 wt%, DER: 6 cm^3/min and BFR: 2 cm^3/min; (b) high porosity HFM: PSf18wt%, DER: 2 cm^3/min and BFR: 0.66 cm^3/min.

The FESEM images that qualitatively give the porosity of the membrane surface were adjusted toachieve the best threshold incorporating the triangle algorithm. For detecting the objectives (pores), FESEM images were converted to binary images and also triangle algorithm was utilized to extract the final real pores from Figures 1 (a) and (b). (some pores were assumed as 'failed' pores and hence were conveniently eliminated for the analysis). An example of the real extracted pores by surface image analysis from FESEM images is shown in Figure 3.

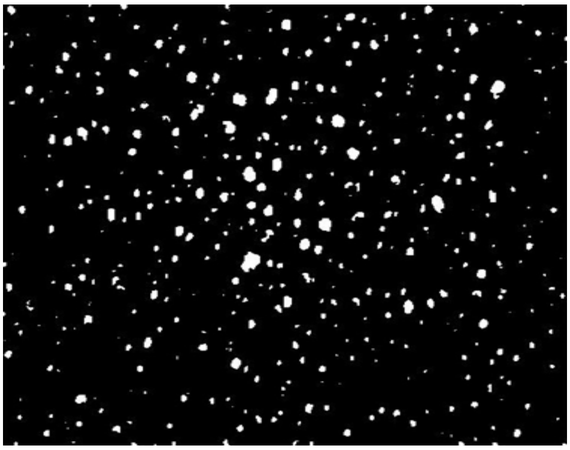
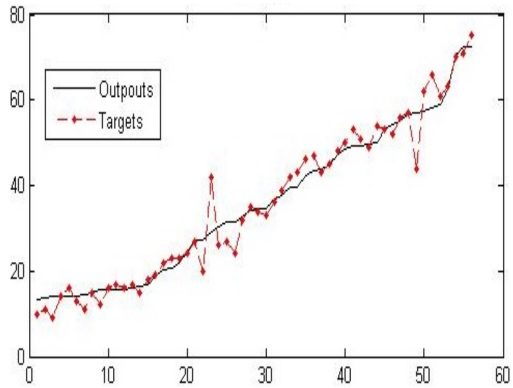


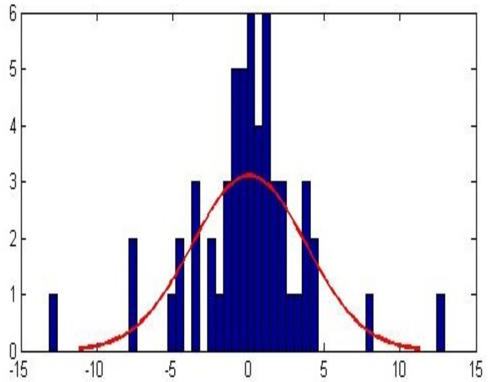
Fig. 3. Real pores extracted by data analyzing result

4.2 Neural network

The surface porosity of the HFMs was obtained by an image processing package (IPP). Afterward, the obtained data were used as the input layer data in the designed ANN configuration. Since the HFM fabrication and characterization are typically difficult and time consuming, only 57 samples were used for designing the ANN. Figure 4 shows the obtained results from the designed ANN with RBF scheme.



(a)



(b)

Fig. 4. Best performances for the RBF network: (a) predicted overall porosity from surface porosity (R=0.984) (b) histogram with fitting line (Mean=0.048 and RMSE=2.73)

Figure 4 illustrates the best performances of the trained RBF network. The corresponding generalization performance of the network shows some small but unrealistic oscillations as can be seen in Figure 4 (a). These fluctuations are due to the noise content of the training data which can be alleviated if the learning algorithm is equipped with some proper noise filtering facility. Based on Figure 4 (b), the mean value is near zero and the root mean square error (RMSE) merit function is also a small value. The results suggest that in order to achieve a higher computational speed, a neural network simulator can be used to replace the earlier models in the process of calculating the membrane porosity. The experimental data and the results of the trained neural network for the overall porosity is shown in Figure 5.

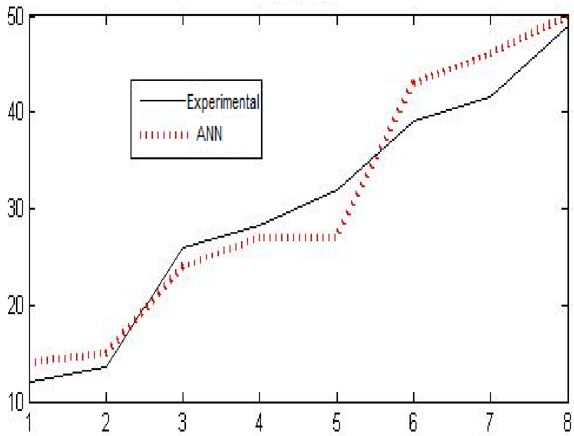


Fig. 5. Porosity prediction of HFM based on the experimental results and the data from trained ANN

As can be seen in Figure 5, the output from ANN is in good agreement with the experimental counterpart, thereby implying that it is capable to predict the overall porosity of HFMs effectively.

5 Conclusions

An image processing package was developed to measure the membrane surface porosity supplying the FESEM images as the input feed with the PSf HFMs spun in various dope compositions and spinning conditions. An ANN method with RBF configuration was utilized and applied to predict the membrane overall porosity. The results obtained by the trained neural network were compared with those acquired through the mathematical model (weight equation). The results were found to be in good agreement, thereby confirming the applicability of the approach for computing the overall porosity of HFM.

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