Environment Protection Engineering

Vol. 34 2008 No. 1

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THE POSSIBILITIES OF MODELLING THE MEMBRANE SEPARATION PROCESSES USING ARTIFICIAL NEURAL NETWORKS

Despite the substantial progress observed in last years in membrane science, many initial problems associated with membrane processes have not been solved, including limitations in ability to control and predict membrane fouling and selectivity. That is why a suitable method for process optimization should be developed which will allow the most important membrane parameters to be modelled.

The paper describes the possibilities of forecasting the parameters of the membrane processes using artificial neural network (ANN). The modelled parameters vary in their properties, so different ANN may be used for their testing and forecasting.

1. MEMBRANE PROCESSES

The development and application of membrane separation processes are among the most significant advances in chemical and biological process engineering. Membrane processes are based on advanced filtration which utilises the separation properties of organic or inorganic films.

In recent years, a substantial increase in the application of membrane processes can be observed in water and wastewater sector. Membranes are used for liquid–solid separation, desalination, softening, removal of organic and inorganic contaminants, disinfection, gas transfer or sludge thickening. Today, very effective membrane processes are capable to replace the majority of separation processes used in environmental engineering. In this area, pressure-driven membrane processes predominate.

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Ranging from microfiltration to reverse osmosis, the pressure-driven membrane processes make the removal of nearly all undesired compounds from a given solution possible (figure 1).

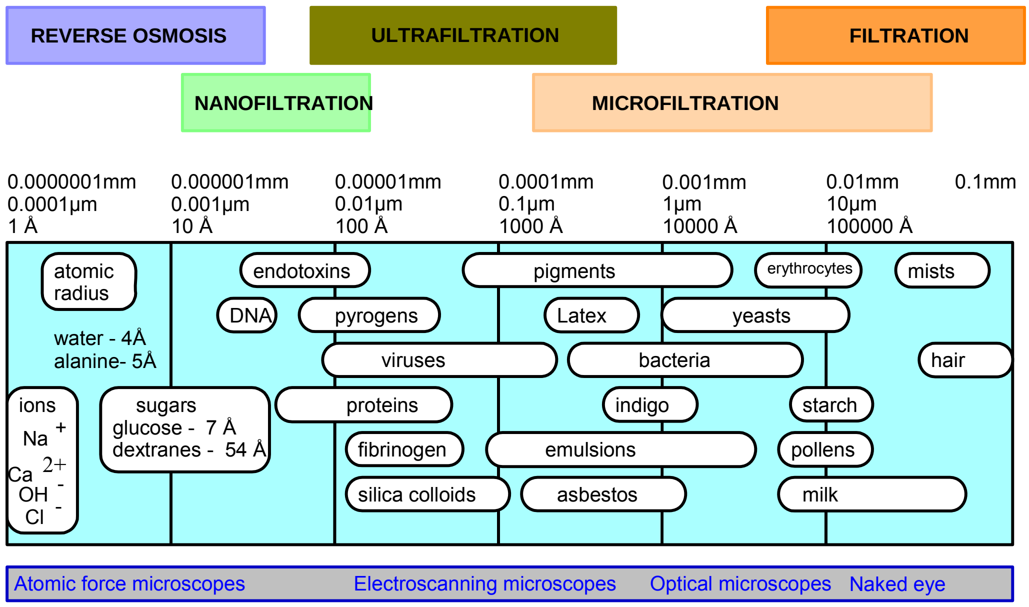


Fig. 1. The range of pressure-driven membrane processes of separation [1]

Despite the substantial progress achieved recently in membrane science, many initial problems associated with membrane processes have not been solved, including limitations in our ability to control and predict membrane fouling and selectivity. That is why a suitable method for process optimization should be developed to model the most important membrane parameters. The method of process modelling based on Artificial Neural Network is recently very popular in chemical engineering. The objective of this paper was to show how ANN can be applied to modelling membrane parameters which are responsible for the efficient separation processes.

2. ARTIFICIAL NEURAL NETWORK (ANN)

The idea of ANN is based on the structure of nervous system that transmits the signals from outside the cell. Neurones (figure 2), the main elements of nervous system, are responsible for the transferring of information. Input signals are carried to the cell by synapse. Output signals are conducted away from the cell body by axon. In the nervous system, nervous impulses from one cell to another are conducted due to special chemical substances called neuromediators. Artificial neural networks try to copy human brain functioning. The intellectual functions of the brain are connected with cerebral cortex that includes 10^{10} nerve cells. The number of interconnections between cells are equal to 10^{15} with the distances of 0.01 mm–1.00 m. The frequency of the transmission of information is estimated on the level of 1–100 Hz, but the time of transmission is equal to 1–2 ms. The above mentioned numbers prove that human brain is really fast and best known natural processor. Information transmission is based on the difference of the action potentials. This action-potential difference arises due to the difference between Na^+ and K^+ ion concentration that occurs when neurones are activated by the external or internal factors.

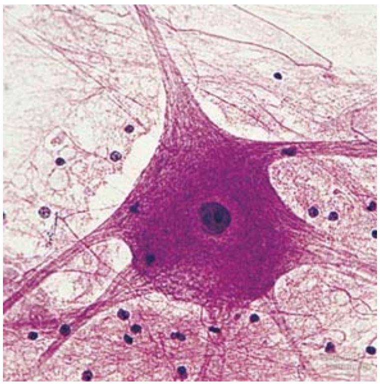


Fig. 2. The image of a natural neuron

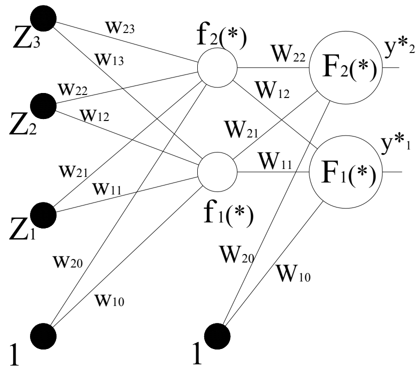


Fig. 3. The image of a multi-layer perceptrone [2]

Artificial neural network is a simplified model of human nervous system. The network consists of neurones which are data processors. Each neurone is responsible for summarizing input signals. ANN just computes output values from input values. The sum of the transferred information is weighted. These weighted connections are shown in figure 3 [2]. The sum of the values is transmitted to the next network layer.

The first model of artificial neurone was constructed by McCulloch and Pitts in 1943. According to MCCULLOCH and PITTS [3] the output signals are expressed by:

$$y_i = f\left(\sum_{j=1}^{N} w_{ij} x_j + b_i\right), \quad i, j = 1, 2, ..., N, \tag{1}$$

where:

y_i – the output signal;
x_j – the input signal;
w_{ij} – the weights between node i and node j;
b_i – the threshold value.

The function $f(u)$, as shown in equation (1), is called the activation function that stimulates the information transmission. The above mentioned model is quite simple and since 1943 ANN has been developed and improved to be sufficient for modelling a lot of dynamic processes. Neural networks enable non-linear and complex problems to be modelled.

Neural networks can be divided into three categories:

• recurrent networks,

• radial networks (RBF),

• feed forward multi-layer perceptrone (MLP) (figure 3) which is the most popular one.

In MLP, neurones form the layers (input, hidden and output layers). The neurones from two adjacent layers are interconnected. The way of transmition is based on different activation functions.

The way of ANN learning is very important, since it has the significant influence on the predicted parameters. There are known two main methods of ANN learning:

• supervised learning,

• unsupervised learning.

In the technical aspects, the first manner is more suitable because of required convergence between experimental and forecasted parameters. The most popular supervised learning is called backpropagation algorithm with the learning coefficient $\eta \in (0; 1)$. This method is based on the negative gradient optimization. The aim is to define the objective function. The derivative (gradient) of this function specifies the weight Δw_{ij} of the first connection between neurones. The algorithm is repeated since $\Delta w_{ij} = 0$. Another way of learning is the graph method that is applied in, for example, recurrent networks.

The modelling using ANN may be quite good manner of predicting membrane parameters. The prediction by ANN approach is dynamic and efficient which is important because of changing parameters during operation time.

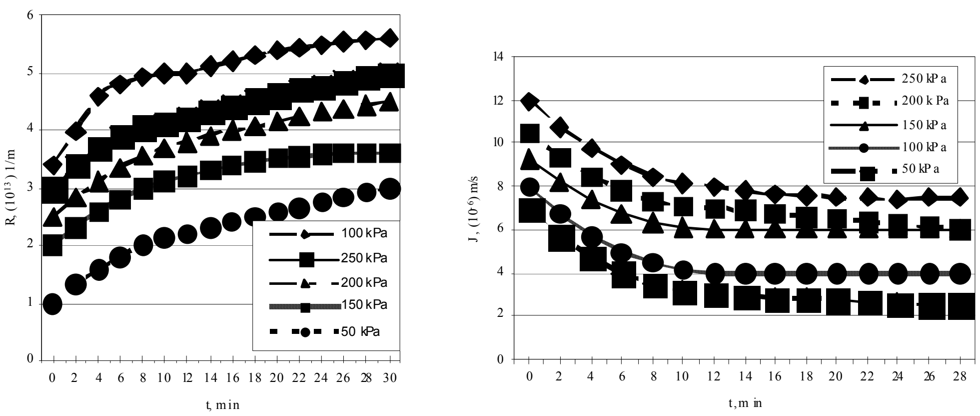
3. APPLICATIONS OF ANN IN MEMBRANE TECHNOLOGY

In this part of the article, the way of ANN applications in the membrane separation processes will be discussed. The most important parameters of ANN and membrane technology will be considered here. In all the papers mentioned below, ANN was computed with the help of MATLAB program and its special toolbox considering neural networks. The most popular activation function used for learning process is sigmoid function

$$f(x) = \frac{1}{1+e^{-x}} . \tag{2}$$

3.1. MEMBRANES IN FOOD INDUSTRY

In 2003, RAZAVI et al. [4] applied ANN to predict the permeate flux *J*, total hydraulic resistance *R* and the rejection of solutes (protein, fat, lactose, minerals and total solids) in the crossflow UF of milk. The conditions of the process have been changing due to the change of the transmembrane pressure (TMP) (51; 101.33; 152; 203 and 253 kPa) and the temperature (30 °C; 40 °C and 50 °C). Feed concentration was constant and the feed flow equalled 15 dm^3/min. In the experiments, they used the polysulfone capillary amide membrane with the cut-off of 20 kDa. The permeate amount was recorded every 30 seconds. The supervised learning of ANN was based on the backpropagation method. The sigmoid function as an activation function, being responsible for a suitable prediction of the outputs, was used. Only 14.2% of data were used for the training, the rest – for validation. In this case, the values were normalised using the linear normalisation method. A single hidden layer with 15 hidden neurones allowed a sufficient convergence between the data predicted by ANN and the experimental ones: *J* decreased with the process time, *R* increased with TMP and temperature; the rejection of solutes estimated by ANN was very similar to that obtained experimentally. The examples of theses results are shown in figure 4. In this case, the authors used for validation 756 points, and for training – 84 points. ANN was successfully used for predicting milk ultrafiltration.



a) b)

Fig. 4. Total hydraulic resistance (a) and dynamic flux (b) predictions during the milk ultrafiltration as the function of transmembrane pressure. Temperature was constant and equal to 40 °C [4]

PIRON et al. [5] have compared ANN, called also "black box", with semi-physical approach in the crossflow microfiltration. "Black box" model does not require any exact description of the process. This method is based on the network capability to approximate the system. On the contrary, semi-physical approach is rather a priori way of approximation. The suspensions of bakers' yeast were used in the experiments performed at different pressures (50; 100; 160; 200; 300; 400 kPa) and different cross-flow velocities (2; 3; 4 m/s) at a constant temperature of 20 °C. MF module used in the test consisted of 7 tubular mineral membranes whose filtration area reached 0.16 m^2. Analyzing the results obtained it became evident that the hydraulic resistance increased with the pressure and decreased with cross-flow velocity. The filter cake formation on the membrane surface was chiefly responsible for these relationships and for this reason force compensation and back transport were analysed. The authors used sigmoid function for the learning and activation processes. The inputs to this neural architecture were: hydraulic resistance, cross-flow velocity, pressure and concentration. The output signal was defined as permeate flux. Figure 5 shows the example of the neural network used. The authors concluded that semi-physical approach (hybrid model) was more precise, and ANN could provide only additional help in accurate computing.

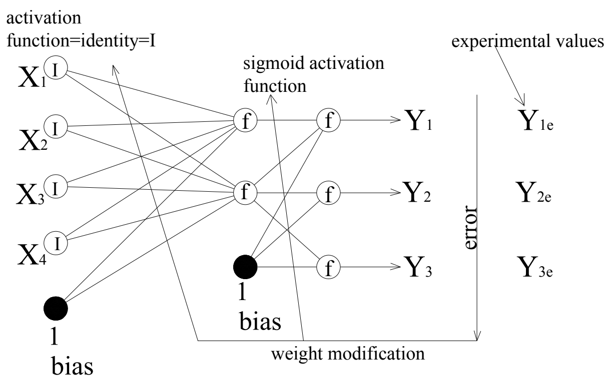


Fig. 5. The image of two-layer feedforward network used by PIRON et al. [5]
to model MF of bakers' yeast [5]

DORNIER et al. [6] dynamically modelled MF membrane fouling caused by a raw cane sugar suspension using ANN. In the experiment, ceramic membrane (1.4 μm pore size) with multichannel profile was used. The experimental setup was connected to computer which enabled the data to be simultaneously computed by ANN. Membrane eouling is a result of the mass flow, back diffusion connected with high feed concentration and electrochemical interactions between membrane and feed solution. In this case, the hydraulic resistance of the membrane was changing with time, but the temperature (80 °C) and concentration were constant. MLP network was designed in such a way as to carry out an accurate simulation being based on backpropagation learning method and the sigmoid activation function. The simulation was run using two series of experimental data. In the first series both pressure and flow velocity had constant values, while in the second series, other values were included in the range of interest. ANN with two and one hidden layers was tested. Finally, a good convergence (97%) was obtained with 5 neurones in the first hidden layer and 3 neurones in the second hidden layer (NN5/3). The experiment and ANN predictions revealed that fouling increased with the duration of the membrane process. Figure 6 shows the comparison between the experimental and calculated total hydraulic resistance (fouling) at the pressure of 150 kPa and the flow velocity of 5 m/s.

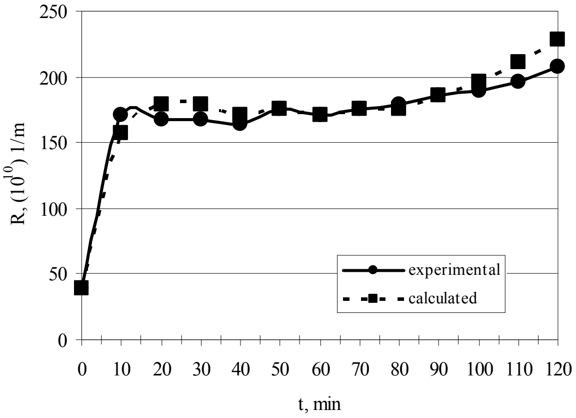


Fig. 6. The comparison between the experimental and calculated total hydraulic resistance (NN5/3) in the microfiltration of raw cane sugar [6]

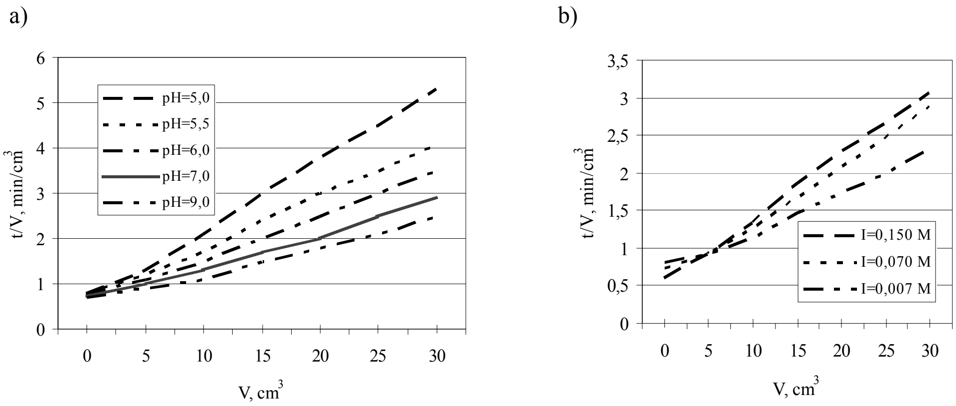


Fig. 7. ANN predictions and experimental points obtained for the ultrafiltration of proteins solution of different pH (a) and ionic strength (b) [7]

ANN was applied by BOWEN et al. [7] to predict the dynamic dead-end ultrafiltration of proteins. The input signals (pH = 5÷9, zeta potential $\xi = -2.62 \div -42.78$ mV and ionic strength I = 0.03÷0.15 M) were measured and based on their values ANN was able to generate the rate of the ultrafiltration which was the output value. The pressure was constant and equal to 400 kPa. This rate of ultrafiltration and the relation between time (t, min) and volume of filtrate (V, cm^3) could be identified. In figure 7, t/V versus V is shown. The curves are becoming steeper with a decrease in pH values and with an increase in ionic strength. According to the authors the quality of the inputs is more important than their quantity. All ANNs used in the work had one single layer. The number of neurones in the hidden layer were estimated by the trial-and-error method. The sigmoid function applied proved to be quite efficient because of its differentiability, continuity and monotonicity. What is more important, the derivative of this function could be expressed by the function itself. The weights of the connections between neurones were minimized by backpropagation method. The authors reached reasonable agreement between the experimental data and the outputs generated by ANN. An average error was less than 2.7%.

RAI et al. [8] applied ANN modelling in ultrafiltration of synthetic fruit juice and mosambi juice in order to predict the permeate flux and total soluble solid in the permeate. To reach this aim, it was necessary to have such inputs as: TMP = 276, 414, 552 kPa, the concentration of both sucrose (10, 12, 14, 11.2%) and pectin (0.1, 0.25, 0.3, 0.5%) in the feed solution, and the duration of the process. In the experiments, composite polyamide UF membrane of 50 kDa cut-off and an effective filtration area of 15.2 cm^2 was used. Sucrose and pectin solution was responsible

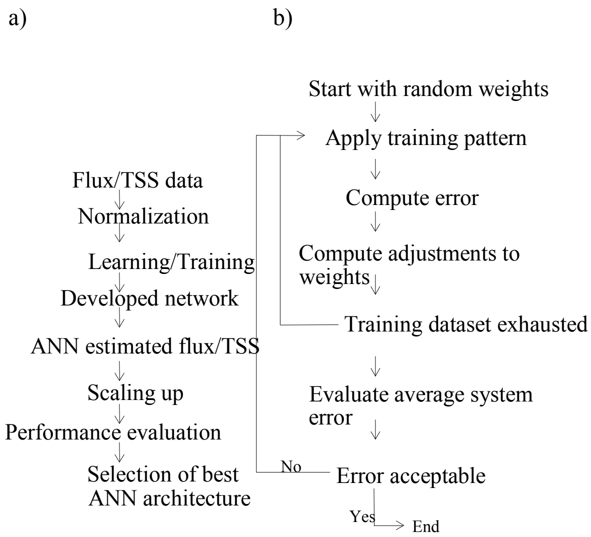


Fig. 8. Methodology of developing MLP (a) and procedure of training MLP (b) for modelling fruit juice ultrafiltration [8]

for the membrane gelation that caused permeate flux decline. It is worth noticing that sucrose was not retained on the membrane, but it made the pectin layer fairly thick which delayed the sucrose transport. In order to model typical feedforward neural network, a sigmoid activation function was used. Learning data were divided into two groups: in the first one the flux is considered, and in the second one – soluble substances in the feed solution. In this case, the network of two hidden layers was the optimal type of ANN. The model of ANN architecture-developing and training procedure is shown in figure 8. The results obtained from ANN and mean absolute error method were compared. The ANN model was sufficient for predicting output signals.

3.2. MEMBRANES IN WATER AND WASTEWATER TREATMENT

Dynamic modelling the crossflow MF of bentonite suspension using recurrent neural network was described by HAMACHI et al. [9]. A recurrent network (figure 9), more complicated than MLP, enabled the forecasting of such parameters as the permeate flux *J* and the deposit thickness e_p. The above mentioned unknowns were predicted on the basis of TMP (P = 50÷300 kPa), cross-flow velocity (u = 0÷0.75 m/s) and the concentration of suspension (c = 0÷0.5 g/dm^3). In the experiment, we applied a ceramic tubular membrane with an external skin. Optical devices and laser beam allowed the deposit thickness to be measured.

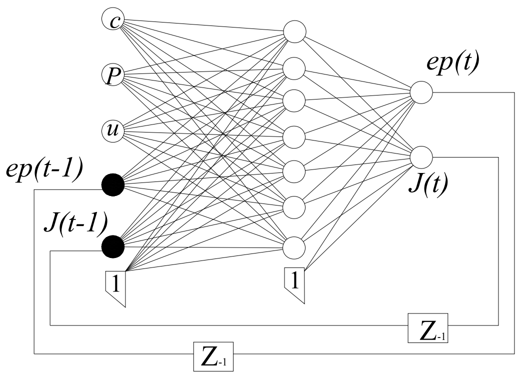


Fig. 9. The structure of recurrent neural network used in modelling the crossflow MF of bentonite suspension [9]

It is obvious that the results generated by ANN showed the same trend as experimental values. Permeate flux was decreased and deposit thickness increased during operation time. To obtain such a convergence it was necessary to choose the range of the input variables properly. The learning method was based on the quasi-Newtonian approach. The model designed by using sigmoid function could satisfactorily predict the output values. All data were divided into two groups: a testing group and a validating group. Single hidden layer with seven neurones turned out to be sufficient for reliable prediction of the parameter.

DELGRANGE et al. [10] have used ANN to predict total hydraulic resistance of the membrane at the end of a municipal water ultrafiltration cycle and after backwashing. The output values such as fouling and hydraulic resistance were connected with the clogging of the capillary modules and adsorption of organic matter on the membrane surface. In the experiment, the rate of permeate flow, pressure and feed water turbidity were used as input signals. Learning process was based on a proper estimation of the weight generated by the inputs. The authors used sigmoid activation function to predict output parameters. In this case, water was pretreated by passing it through 200 μm filter. Figure 10 shows the schema of a pilot plant. This figure is quite important because it shows that before the membrane processes it is necessary to pretreat (for example, by typical filters) the raw solution, otherwise UF membrane would be plugged earlier and backwashing would be more frequent. Modelling showed that for the prediction of reversible fouling water turbidity was an efficient parameter.

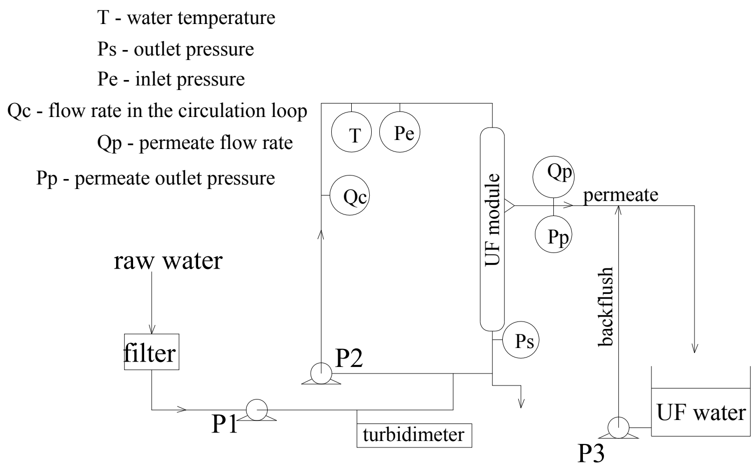


Fig. 10. Schema of the pilot plant used in ANN modelling of water ultrafiltration [10]

DELGRANGE-VINCENT and co-workers [11] designed ANN model responsible for predicting reversible and irreversible fouling of UF membranes used for drinking water production. The model was based on two interconnected (but trained separately) recurrent neural networks (figure 11).

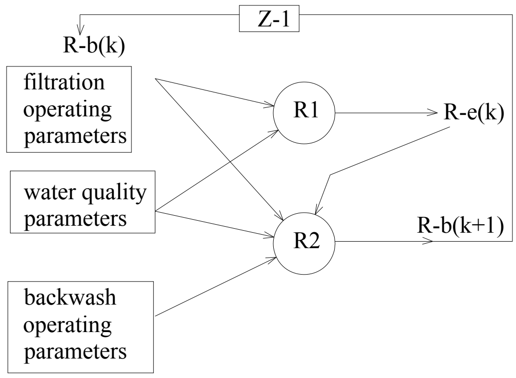


Fig. 11. The structure of interconnected neural networks designed to predict reversible and irreversible fouling of UF membranes used for drinking water production [11]

During long-term prediction (more than 100 filtration cycles) of fouling, water quality and process parameters were changed. The authors noticed that in the construction of ANN models, permeate flux, time of filtration, turbidity, dissolved oxygen concentration, pH, UV absorbance and pressure of backwashing proved to be very important. These parameters were used as input values. The results showed that irreversible fouling was rapidly increasing when permeate flux reached the values of 70÷80 $dm^3/h{\cdot}m^2$. Figure 12 presents the resistance *R* of an experimental membrane after a number of cycles.

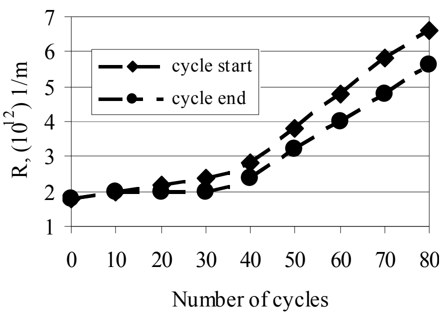


Fig. 12. The changes in the resistance of the membrane used in natural water ultrafiltration after a number of cycles [11]

In other experiments, DELGRANGE et al. [12] made attempt to predict the changes in TMP during ultrafiltration. They carried out the next analysis more comprehensive than the first one, and in this case the input signals (very important for efficient ANN) were as follows: flow rate (250÷700 dm^3/h), turbidity (0÷100 NTU) during the cycle, and temperature (5÷15 °C). These parameters were measured on-line, but such parameters as UV absorbance and total organic carbon concentration (TOC) being measured only pointwise. The experiment with drinking water was performed on the cellulose acetate hollow fibre membranes. The schema of the pilot plant was the same as in other authors' experiments (figure 10). The sigmoid activation function applied to one hidden layer accurately estimated all parameters. According to Delgrange et al. water turbidity proved to be the crucial parameter responsible for the learning and training of ANN.

CABASSUD et al. [13] described the algorithm for the control of the drinking water production from raw surface water. The objective of their work was to avoid irreversible fouling of membrane. To reach the target the authors designed two networks. One of them modelled hydraulic resistance at the beginning of the cycle of ultrafiltration, while the other one – at the end. The networks have been learning separately. The input values for the first network were as follows: feed water parameters and resistance during this cycle of filtration. For the second network the input value was based on the resistance at the end of filtration calculated by the first network. In this work, the authors made use of the results obtained previously [11], [12]. The results of pilot plant experiments were compared with these obtained under industrial conditions.

SAHOO and RAY [14] analyzed the prediction of the flux decline in crossflow membrane filtration of water containing colloidal particles, proteins, macromolecules and biological particles. They investigated a decrease in the permeate flux under different conditions and at changeable values of water physicochemical parameters. The aim of the work was to compare the results generated by ANN with those generated by genetic algorithms (GA). It was shown that GA prediction for permeate flux decline was more accurate than that of ANN model, calibrated using trial-and-error method. A radial function with two hidden layers was defined to compute output values. A total mean square error calculated based on GA and ANN allowed a valid comparison in each iteration to be made.

SHETTY and CHELLAM [15] described the possibilities of predicting membrane fouling by using ANN. In their work, surface water and groundwater were purified using nanofiltration. As the inlet parameters for ANN they chose feed flow and water quality (pH, UV, total dissolved substances and temperature). These parameters changed, depending on the type of membrane, season and the place of sample collecting. The examples of these values are given in the table.

In ANN learning, they used the sigmoid function for the hidden layers and linear functions for the input and output layers. The Levenberg–Marquardt algorithm was employed for ANN training. In the experiments use was made of the flat-sheet and spiral membrane modules. Modelling by ANN brought about sufficiently good results, but it was important to take account of the concentration of colloids and bacteria in the calculations.

Table

Summary of pilot and full-scale experiments used in ANN learning [15]

Location	Water source	Feed water quality				Pretreatment	Membrane
		pH	TDS, mg/dm^3	UV_{254}, 1/cm	*T*, °C		
West Palm Beach, FL	Floridian aquifer	5.80–7.2	291–338	0.46–0.509	23.1–25.8	pH adjustment using H_2SO_4; 1.0 mg/dm^3 anti-scalent addition; 5 µm cartridge filtration	TFC (Koch fluid systems, San Diego, CA)
Boyton Beach, FL	Well water	5.9–6.53	595–617	0.369–0.489	23.3–25.5	pH adjustment using H_2SO_4; 5 µm cartridge filtration	NF70 (Dow FilmTec, Mid-land, MI)
Boca Raton, FL	Biscayne aquifer	5.7–6.75	349–408	0.186–0.465	24.2–25.6	pH adjustment using H_2SO_4; 4.0 mg/dm^3 anti-scalent addition; 5 µm cartridge filtration	NF200-4040 (Dow FilmTec, Midland, MI)
Dayton Beach, FL	Floridian aquifer	5.6–7.12	330–408	0.26–0.308	20.6–23.9	pH adjustment using H_2SO_4; 3.0 mg/dm^3 anti-scalent addition; 5 µm cartridge filtration	BW30-4040 (Dow FilmTec, Midland, MI)
Deltona, FL	Floridian aquifer	5.91–6.96	180–280	0.083–0.089	20.2–27.4	pH adjustment using H_2SO_4; 5 µm cartridge filtration	TFC (Koch fluid systems, San Diego, CA)

SHETTY et al. [16] studied the prediction of the contaminant removal from surface and groundwater in nanofiltration process. Their attention was focused on the retention of dissolved organic carbon, precursors of total organic halides, four trihalomethanes, nine haloacetic acids and total dissolved solids. In order to model the above mentioned complex problem, the inputs such as flux (10÷35 dm^3/h·m^2) and feed water quality parameters (pH, total dissolved solid concentration, a surrogate for ionic strength) were used. At the beginning of the process, the ratio of C_p/C_f, i.e., the ratio of the permeate concentration to the feed concentration of each contaminant, affected greatly the retention. Then in the calculations by ANN, the normalized ratio of C_p/C_f was also predicted. During the learning of neurones in two hidden layers (a typical sigmoid activation function) of ANN, Shetty et al. employed the backpropagation method with the Levenberg–Marquardt algorithm. For each contaminant, different ANN model was designed The results showed that ANNs could model the rejection on NF membranes, using very heterogeneous compound.

BOWEN et al. [17] made use of ANN modelling to predict salt rejection (NaCl, Na_2SO_4, $MgCl_2$, $MgSO_4$) at nanofiltration spiral-wound membrane modules. In the experiment, temperature and cross-flow were constant and could not be treated as input variables. As the input signals the transmembrane pressure, salt feed concentration, pH and the kind of the salt were used. The way of learning was estimated by a typical sigmoid activation function. The agreement between ANN and experimental data proved to be satisfactory. The results showed that rejection increased, depending on operation conditions, and that the salt rejection in the mixtures of monovalent and divalent anions was more reliably predicted by ANN than by the experiment. NaCl rejection, calculated by ANN and measured during NF at variable pH of solution, is shown in figure 13.

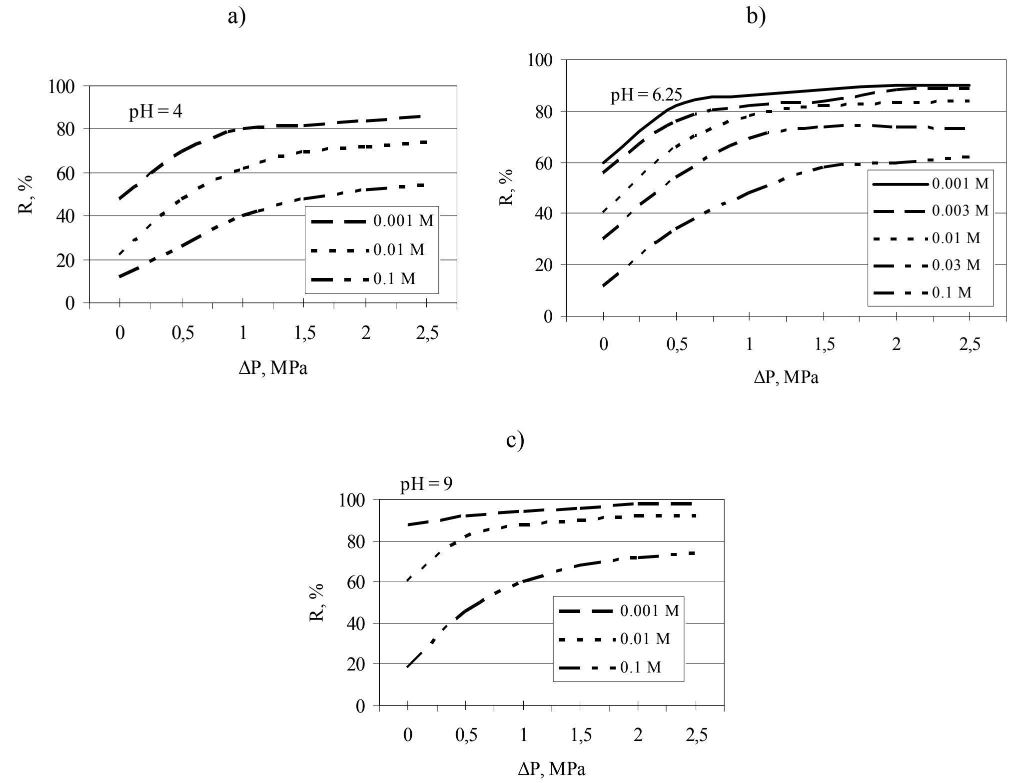


Fig. 13. ANN predictions for NaCl rejection as a function of salt concentration and pH:
a) pH 4, b) pH 6.25, c) pH 9 [17]

BOWEN et al. [18] estimated the rate of crossflow ultrafiltration using ANN approach. They examined the removal of colloidal silica suspension at different pH values (4÷9), ionic strength (0.0077÷0.072 M), zeta potential (–80.5÷ –6.3 mV) and pressure (40÷300 kPa). These three groups of data were used for learning, testing and validating ANN. In the experiment, they used the membrane made from polyethersulfone with a 30 kDa cut-off. The problem was non-linear and complex, that is why the modelling with help of ANN being applied. A typical sigmoid activation function in one hidden layer was used for learning the network. The researchers aimed to predict the changes in permeate flux with time. Silica particles could be treated as representative of other charged particles as well as of inorganic, polymer and biological matter. This aspect of representation was considered during designing the neural network, which allowed a high compatibility between experimental data and the data generated by ANN to be achieved.

CHEN and KIM [19] used a radial basis function for predicting the permeate flux decline during crossflow filtration of colloidal suspension. They tried to compare the results of, radial networks (RBF) with those of both backpropagation method and linear regression method. In a radial network, tan-sigmoid function

$$f(x) = \tan \frac{1}{1+e^{-x}} \tag{3}$$

was used as activation function. The input values such as TMP (*P*), the time of filtration (*t*), the radius of the rejected particles (*PS*), pH and ionic strength (*IS*) were chosen quite precisely. Figure 14 shows schematically the architecture of the network applied. The parameters b_i, called biases, are responsible for the training process. Only 17% of data were used for training, the rest was responsible for validation. As expected, permeate flux decreased with the time of operation and also was changing, depending on pH value. The possibilities of applying the modelling to industry by using RBF seem quite serious because the results obtained by CHEN and KIM [19] are accurate and sufficient.

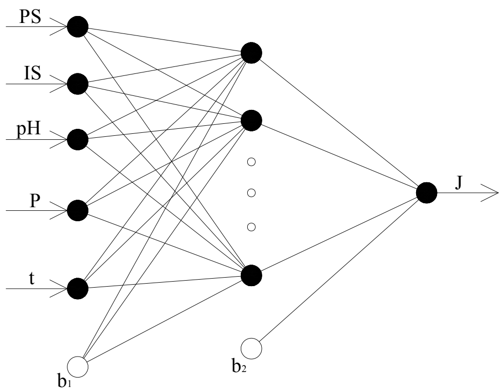


Fig. 14. The architecture of the neural network with one hidden layer used for predicting the permeate flux decline during crossflow filtration of colloidal suspension [19]

CURCIO et al. [20] analyzed flux decline during the ultrafiltration of BSA solution, using a polyethersulfone membranes with a 20 kDa cut-off. The ANN approach applied allowed us to predict the permeate flux. The experiment was carried out under pulsating conditions which were important for dynamic modelling. They dealt with such conditions (pulse duration of 10 s) when the valve EV_4 was periodically open and closed (figure 15). In those investigations, these pulsating work conditions seemed extremely interesting because all changes were measured on-line. Neural network had the architecture based on the MLP with two hidden layers in which neurones were trained by a typical sigmoid activation function. TMP was not considered to be the input value because it had not significant influence on the output value. ANN consists of three input signals, i.e., time, flow (0.12÷0.36 m^3/h) and operation time (60÷120 s). The output is defined as normalized permeate flux.

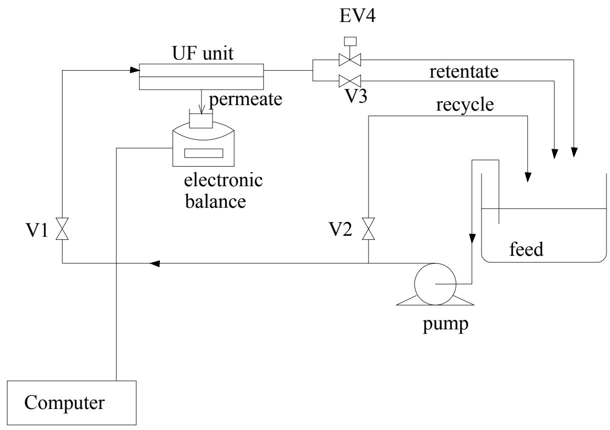


Fig. 15. Schema of pulsating TMP ultrafiltration plant used for BSA ultrafiltration [20]

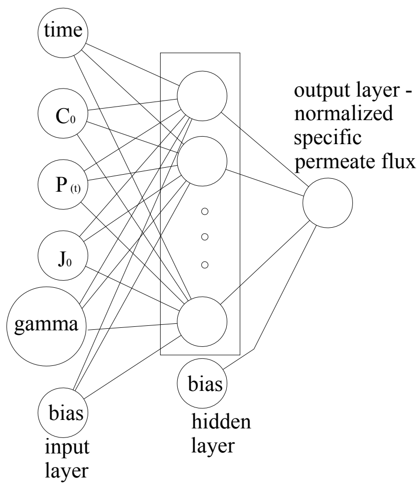


Fig. 16. The structure of ANN used for prediction of normalized permeate flux during microfiltration of polydispersed suspension [21]

CHELLAM [21] used ANN model for the prediction of fouling and normalized permeate flux during microfiltration of polydispersed suspension (glass and silica). The greater the initial permeate flux, the bigger the changes in the morphology of filtration cake and hydrodynamic parameters of specific resistance that was quite important for the range of fouling. The model included the input signals feed concentration (C_0), initial permeate flux (J_0), entrance shear rate (γ), instantaneous transmembrane pressure ($P_{(t)}$) and filtration time. During the training the use was made of the Levenberg–Marquardt algorithm. Figure 16 shows the structure of ANN as well as the input and output values used by the author [21].

At the beginning of the process, the permeate flux was the most important parameter influencing the fouling. Chellman employed different kinds of networks, depending on the changes in the type of suspension. The more complex the suspension, the longer the time of learning. The results showed that using ANN model it is possible to obtain better effects based on the nonlinear and dynamic parameters than using previous mechanistic models.

ZHAO et al. [22] discussed the prediction of water quality after RO and NF. The aim of their work was to compare the results obtained from modified solution diffusion model with those obtained from ANN. They used two different networks: the first based on MLP and the second based on RBF. The authors concluded that hybrid numerical model and ANN used together were able to make the prediction of membrane performance more reliable.

NIEMI et al. [23] modelled using ANN the separation of ethanol and acetic acid in reverse osmosis and ultrafiltration of bleachery effluent. The neural model was built in order to predict permeate flux and rejection at changeable process parameters such as: temperature, supericial flow velocity, pressure and concentration of solute. In this case, chemical oxygen demand and permeate flux were the input values of ultrafiltration. The network consisted of one hidden layer with neurones trained by a sigmoid activation function. The Levenberg–Marquardt method was used for interpolation. The accuracy of calculations proved to be sufficient and time of computing reduced using ANN approach. The results obtained using ANN were compared with those based on the mass transfer model and it turned out that the predictability of output variables using ANN was almost the same as that obtained using finely porous model.

AYDINER et al. [24] analyzed phosphate removal by fly ash which was separated using crossflow microfiltration membranes (anisotropic cellulose acetate and cellulose nitrate). The experiments were performed at cross-flow velocity of 5.2 m/s and a constant temperature of 20 °C. The aim of the paper was to predict flux decline in the operation time. For this purpose the authors compared the results obtained using ANN (two networks NN1 and NN2 were designed) with the Kołtuniewicz method being based on the surface renewal model (two types K1 and K2) [24]. The Kołtuniewicz model was used for the stochastic nature of the cake on the membrane. In the experiments based on the Kołtuniewicz model, an average error of prediction exceeded 10%. Variable values of transmembrane pressure and the concentration of pollutants were used as inputs for ANN. ANN was built from one to four hidden layers with a changeable number of neurones and trained with the help of backpropagation algorithm. This approach was more compatible with experimental data than the Kołtuniewicz model. The error distribution, responsible for the compatibility between experimental and predicted data, is given in figure 17 which presents the information allowing the comparison between two above mentioned models.

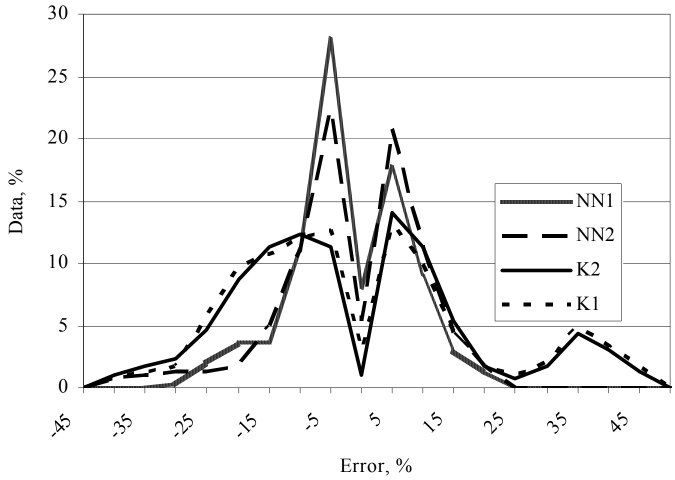


Fig. 17. The error distribution of all the data predicted by ANN and the KOŁTUNIEWICZ method [24]

Based on ANN TEODOSIU et al. [25] tried to predict membrane flux before and after backwashing in dead-end flow ultrafiltration of refinery wastewater. Hollow fibre membrane modules with capillary membranes of the cut-off equal to 150 kDa were used. Each membrane module with membranes made from polyethersulphone and polyvinylprolidone had 50 fibres. The internal fibre diameter was 1.5×10^{-3} m and membrane area was equal to 0.1 m^2.

TEODOSIU et al. [25] built two ANN models: one describing flow during UF as a function of time and initial permeate flux value and another describing flow after backwashing. This approach made a global description of flux evolution with time possible. As authors have forecasted, the permeate flux decreased all the time of the process. The learning of the network was based on the backpropagation method, adaptive learning rate and momentum. The use of ANN approach led to relatively small errors (figure 18). The model could be adapted to other membrane technology conditions which is of a real importance for both science and industry.

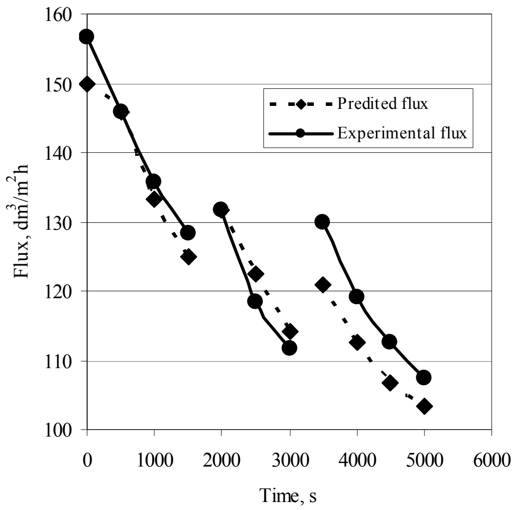


Fig. 18. ANN approximation for backwashing cycles [25]
in ultrafiltration of refinery wastewater

3.3. MEMBRANES IN GAS SEPARATION

SHAHSAVAND et al. [26] compared radial basis function (RBF) with multi-layer perceptrone (MLP) in modelling membrane processes using hollow fibre membranes made from polyphenylene oxide and carbon-type polyimide. The aim of the experiment was to separate carbon dioxide from methane. The experimental setup is shown in figure 19.

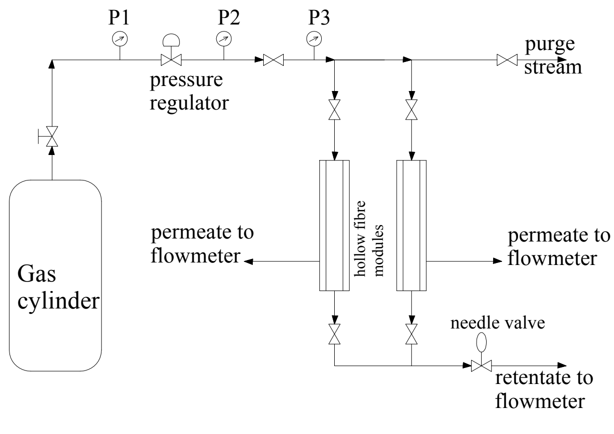


Fig. 19. The schema of membrane system used in gas separation [26]

It was shown that the predictions made by RBF (as more complicated network structure) turned out to be more reliable compared with those of MLP. On the other hand, the predictions of MLP were also compared with experimental data and the convergence was quite high. The authors considered and modelled the disturbances during membrane processes and during learning of ANN and proved that the parameters chosen properly for the regularization of the network were crucial in this investigation.

4. CONCLUSIONS

ANN proved to be an efficient tool for the modelling of different membrane parameters. Since 1990, a lot of investigations have been done using this way of forecasting the membrane processes. The aspects shown in the paper will be examined in the future, because the modelling techniques connected with ANN and membrane technology are evolving all the time. As could be seen, the possibilities of using neural networks for technical forecasting are really great and beneficial because of a simple way of experimental applications. The crucial point in this topic is a huge number of experimental data that must be collected. This is very important for the learning and validating of network structure.

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MOŻLIWOŚCI MODELOWANIA PROCESÓW SEPARACJI MEMBRANOWEJ Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

Pomimo znaczącego w ostatnich latach rozwoju technik membranowych pozostało jeszcze wiele problemów związanych z procesami separacji, a także ograniczeń w kontrolowaniu *foulingu* i selektywności membran. Dlatego konieczny jest rozwój metod optymalizacji, które umożliwiają zamodelowanie najważniejszych parametrów procesów membranowych.

W artykule opisano możliwości prognozowania parametrów procesów membranowych z użyciem sztucznych sieci neuronowych. Właściwości modelowanych parametrów są zmienne, dlatego do testowania i prognozowania użyto różnych typów sieci neuronowych.