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Soft computing techniques in modelling of membrane filtration system: a review

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ABSTRACT

The complexity of the membrane filtration system is due to membrane fouling problem, which reduce the performance of the system. This is the most challenging issue for further membrane control system design and applications. Pursuant to the understanding of different mechanisms of fouling, various modelling approaches have been explored. Modelling of membrane bioreactor filtration system has been extensively employed for the purpose of predicting dynamic behaviour of the process. The application of soft computing in solving real-life problems has become an upward trend nowadays. This paper reviews on the application of soft computing techniques to model, predict and optimize the membrane bioreactor filtration system. A brief review on membrane filtration process for reverse osmosis and other related solid liquid separation processes is also given. Due to the non-linearity of the filtration process and almost impossible to represent it using standard mathematical equation, the application of artificial intelligent based models such as neural network, knowledge-based, fuzzy system and adaptive neuro-fuzzy is investigated and reviewed. For better prediction of models, the application of soft computing tools in the framework of optimization scheme such as genetic algorithm, particle swarm optimization, gravitational search algorithm and hybrid are also reviewed.

Keywords: Membrane filtration; Membrane bioreactor; Soft computing; Artificial intelligent; Optimization; Review

1. Introduction

Membrane filtration technology is an essential technology that has increasingly been employed for the last 25 years and which are expected to continue its important role in future water and wastewater treatment. Due to a rising demand of efficient water and wastewater treatment, the need for sustainable water and reuse of water has significantly increased. Various industries including wastewater treatment plant, water desalination and purification and food manufacturing have received many benefits from membrane filtration technology. Today, with more stringent effluent requirement due to environmental problem and water protection awareness, the membrane is one of the promising filtration techniques capable in resolving these issues. In water treatment, the use of membrane filtration system (or membrane processes) involves with various performance characteristics which depend on the size of species separated [1]. These membrane processes, such as microfiltration (MF), ultrafiltration (UF), nanofiltration (NF) and reverse osmosis (RO) are the technologies generally used in water desalination and purification. In wastewater treatment, the technology used relies on microorganisms suspended in the wastewater to treat it [2]. The MF technology is commonly used for membrane bioreactor systems (MBRs) with both hollow fibre and flat sheet submerged

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membrane bioreactor (SMBR) configurations, overcomes many of the limitations of conventional wastewater systems. The UF technology is often used in cross flow MBRs. These systems have the advantage of combining a suspended growth biological reactor with solids removal via filtration.

These technologies are however, limited in their applications because of membrane fouling. Fouling is a major constraint in membrane process and this problem becomes one of the critical considerations to any industry when investing in this technology. The types of membrane fouling in general can be categorised into colloidal fouling (clays, flocs), organic fouling (oils, polyelectrolytes, humics), scaling (mineral precipitates) and biofouling (bacteria, fungi) [1] and their relative effects depends on the specific applications. To face with this major challenge, a review on modelling of membrane processes (for specific types of membranes) is performed. The review will be helpful in identifying research for the development of improved fouling control techniques based on control and optimisation area of interest. Here, a comprehensive review of modelling of MBR processes discussing the latest research work of soft computing techniques is given. A brief review on modelling of other membrane processes including RO is also given.

MBR system is a complex process which affects numerous parameters including the operation, influent properties and the membrane itself [3]. In the operational point of view, fouling can be controlled and reduced using various techniques such as air bubble (aeration) control, backwashing, relaxation and chemical cleaning. Even though these techniques are unable to resolve the fouling problem completely, an implementation of effective control system and measurement can be utilized to enhance the membrane filtration performance. A thorough understanding on the effectiveness of the techniques in controlling fouling in the membrane filtration operation must be grasped since the approaches will be ineffective if the coordination of the methods is not properly strategized. Each of the method highlight an optimum condition to remove or delay the fouling development. Without clear understanding of the suitable method and its optimum operation performance, the operators will suffer from inefficient filtration process which can cause high energy consumption [4]. Understanding the dynamic and prediction performance of membrane processes is very important because with that information the operation and control of membrane process can be done more effectively in future. In general, modelling and prediction of dynamical system is not new. Researchers have adopted various type of modelling techniques in representing the systems [4–6]. Kinetic and energy model equation is example of standard mathematical equation that widely used in process industries. However, in membrane filtration system, the process is highly nonlinear and uncertainty, and almost impossible to represent it using standard mathematical equation due to the complexity of fouling behaviour [6].

Most of the researchers discusses on the optimisation of operating conditions in reducing and preventing the fouling mechanism, thus reduce the operational cost due to membrane replacement [7,8]. Control systems have already been proven for optimizing operational costs and effluent quality for conventional systems [9]. Hence, good models by taking dynamic behaviour and system configuration into account lead to better conclusions of quantifying operational costs for membrane processes.

Soft computing tool is an innovative approach to construct computationally intelligent systems, where the precise modelling and prediction methods are incapable of giving tolerance for uncertainty, robustness and low solution cost for membrane processes. Soft computing encompasses a group of methodologies, mainly contributed by artificial intelligent (AI), evolutionary algorithm (EA), expert system and metaheuristic, which provide a reliable and flexible information processing capabilities to solve real life problems [10,11]. Besides genetic algorithm (GA) which fall under EA method, particle swarm optimization (PSO), gravitational search algorithm (GSA) and the hybrid PSO-GSA are among well-known soft computing tools in the application of MBR systems. The AI algorithm is a wide-ranging group of techniques such as artificial neural network (ANN), knowledge-based systems, fuzzy systems, adaptive neuro-fuzzy (ANFIS), wavelet, support vector machines, pattern recognition, etc. These algorithms can be categorized as a nonlinear black box modelling technique. For a linear black box modelling, system identification technique such as autoregressive model with exogenous input, autoregressive-moving average with exogenous input, output error and box jenkins could also be used in the modelling a membrane process.

The AI techniques have been rapidly grown year by year with a more sophisticated algorithm as well as the reliability of the structure to give better performance regarding modelling and prediction. In the crossflow MF membrane process, the AI based techniques were found very practical in modelling the system [12]. The most common soft computing tools (i.e. ANN, ANFIS, GA, PSO, GSA and the hybrid method) applied in membrane processes as mentioned in [13–15] and will be further discussed in this paper. In summary, the membrane processes and its parameters for modelling and prediction is given. Then, a comprehensive review on the application of soft computing tools using ANN models is presented. Other soft computing techniques including knowledge-based system, ANFIS, fuzzy system modelling and optimizations applied in membrane processes are highlighted. The combination of ANN with other soft computing techniques in improving the prediction accuracy is also discussed. Finally, the review is concluded by suggesting the suitable algorithm for membrane processes and a way of improvement when dealing with complex fouling behaviour.

2. Motivation for modelling of membrane filtration processes

Modelling and prediction of membrane filtration processes can be divided into various parts of the system and it depends on the application and purpose of the model. Most of the membrane filtration models discussed in this review are focused on the application into plant design, control and optimisation. Fouling phenomena in membrane filtration processes is complex and involved many variables. Mathematical modelling of membrane fouling process will be helpful for technical expert or engineers to improve design and operation of membrane water and wastewater treatment facilities (UF, MF, NF, RO). In general, mathematical models like activated sludge models (ASMs) are widely used for studying process behaviour, system design and process optimization in the conventional wastewater treatment [16,17]. In a modern water and wastewater treatment like membrane processes, most researchers also captured membrane fouling phenomena in the form of mathematical models [18]. Several works have been attempted to predict membrane fouling through the use of mathematical models, both for mechanistic (or analytical) and empirical (or system identification) approaches [19–23]. Many of the mechanistic modelling approaches often suffer from the complexity of membrane fouling that requires expert knowledge of the processes. Moreover, it involves interconnection reasons and its knowledge still vague. Darcy's law approach in [23] for instance, employs the series of resistance to show the various types of blocking in the MBR filtration process including initial membrane resistance, the cake layer, pore blocking resistance and etc. However, this model not suitable for control application because of the complexity on each of the resistance measurement.

As mentioned, modelling and good prediction of membrane fouling is crucial especially for the development of improved fouling control techniques based on optimisation of operating conditions. In the conventional control of membrane process, fouling can be measured via the decline of flux [24] and rapid increment of transmembrane pressure (TMP) in the filtration cycle [25]. Fouling can also result from the increment of hydraulic resistance in the filtration process [26,27]. Previous modelling studies of membrane fouling to optimise a real treatment plant have been comprehensively discussed by Paul [28]. In this work, the high accuracy of MBR modelling has improved membrane operation and performance and eventually develop a long-term energy saving control strategy. Modelling and prediction of UF water and surface water presented in [29] provides an improvement in water production. Several improved models of membrane fouling can be found in [27,30,31] which showed modelling of membrane fouling will be useful in the development of improved fouling control techniques. The efficient use of fouling control strategies can helps to reduce the energy demand and other operational costs associated with fouling.

2.1. Factors affecting membrane fouling

There are many factors affecting membrane fouling such as membrane type, hydrodynamic conditions, biological system, bioreactor operating conditions and chemical system [2]. These parameters can be considered for reduced fouling strategies in membrane processes in order to determine the process performance like membrane flux, effluent quality, and pressure drop as well as process economics. The determination of parameters to be optimized in modelling and prediction of membrane processes is crucial and this also depends on the purpose of the models. Table 1 provides basic parameters of membrane processes that usually include biological and nutrient removal parameters such as chemical oxygen demand (COD), biological oxygen demand (BOD), dissolve oxygen, nitrogen, phosphorus, and mixed liquor suspended solids (MLSS). However, other suitable parameters could be considered depending on the type of effluents (industrial, household etc.). General basic parameters usually used to determine the efficiency and prediction performance of membrane is presented in Table 1. In addition to the biological parameters, the filtration unit and operations of fouling control also take place such as the backwashing, the relaxation and the chemical cleaning. These operational parameters can also be modelled to optimize the process scheduling and effectiveness of the process.

Table 1
Basic parameters of modelling and prediction in membrane filtration systems

Input-output parameters	
Chemical oxygen demand (COD)	Transmembrane pressure (TMP)
Biological oxygen demand (BOD)	Membrane surface
Dissolved oxygen (DO)	Filtration time
Nitrogen	Relaxation time
Phosphors	Backwash
Mixed liquor suspended solid (MLSS)	Recirculation flow
Influent concentration	Fouling resistance
Permeate flux	Pump speed
	Input flow rate
	Cleaning regime

In general, the selection of the parameters depends on the types of effluent and the membrane used. In [32], the UF is implemented prior to RO membrane for an industrial wastewater and the parameters involved are suspended solid, COD, BOD and turbidity. Another implementation of UF membrane for industrial wastewater can be seen in [33–35]. In [27], the UF is applied for an industrial water with the parameters included turbidity, TMP, filtration time and cake resistance. The submerged MBR with NF membrane type is implemented for an industrial wastewater effluent by Muhammad et al. [36] considering the parameters such as COD, total suspended solid (TSS), permeate flux, colour and turbidity. Another works on MBR with MF membranes were discussed in [37,38]. The implementation of NF membrane for an industrial water is discussed by Arefi-Oskoui et al. [39]. The work by Avarzaman et al. [30] presents the performance of NF and RO for the application into food industry effluent. Table 2 provides a summary of input-output parameters applied in different membrane filtration systems, which related to the modelling and prediction of membrane processes.

3. Soft computing tools in membrane filtration

In this section, the application of soft computing tools in modelling and prediction of membrane filtration systems will be described further. This section highlights the available tools, mainly related to the AI techniques and several optimization methods that have been successfully applied in the MBRs. Other membrane filtration systems are also

Table 2
Summary of parameters used in modelling and prediction of membrane processes

Author/s	Membrane filtration systems	Parameters	Type of effluent
Ahmad et al. [32]	Ceramic tubular membrane – UF/RO	SS, COD, BOD, turbidity	Industrial wastewater
Ahmad et al. [33]	Tubular module – UF (polyvinylidene difluoride (PVDF)/RO)	Water recovery, colour, odour, turbidity, total dissolved solid, oil and grease, mineral, heavy metal	Industrial wastewater
Nazatul Shima et al. [35]	Dead-end Filtration – UF	Pressure, stirrer speed, permeability	Industrial wastewater
Abdurahman and Azhari [34]	Cross flow MBR – UF	COD, BOD, hydraulic retention time (HRT), sludge retention time (SRT), MLSS	Industrial wastewater
Neoh et al. [38]	Submerged MBR –MF	Temperature, MLSS, mixed liquor volatile suspended solid, DO, HRT, SRT, airflow	Industrial wastewater
Zakariah et al. [37]	Submerged MBR-microfiltration MF	Permeate flux, TMP, airflow, voltage for pump	Industrial wastewater
Muhammad et al. [36]	Submerged MBR- NF	COD, total suspended solid (TSS), colour, turbidity, permeate flux	Industrial wastewater
Chew et al. [27]	UF membrane	Turbidity, TMP, Filtration time, cake resistance	Industrial water
Arefi-Oskoui et al. [39]	Nanolayered double hydroxide (NLDH)/ PVDF nanocomposite membranes	Pure water flux, protein flux and flux recovery ratio	Industrial water
Avarzaman et al. [30]	Cross-flow membrane NF/RO	Permeate flux, transmitted membrane pressure, feed flow rate, processing time, membrane pore size, and membrane type	Food industry

discussed in brief. The AI based modelling required an empirical (input-output) data before the model development. The AI algorithms presented in this section included ANN, knowledge-based systems, fuzzy systems, ANFIS and wavelet. The ANN is the most popular algorithm applied in membrane filtration modelling and will be discussed in details, followed by implementation of other algorithms in briefs.

3.1. Artificial neural network modelling

A ANN algorithm has been proven to be useful and beneficial in many process industries [40,41]. ANN is one of the most popular soft computing methods which usually implemented in the nonlinear applications where the empirical data or input-output relationship is needed. As the development of ANN algorithm progresses until now, it can be seen that each ANN has its own structure and network topology. In terms of modelling of MBR filtration, remarkable progress has been made in the last few decades to improve MBR filtration using ANN-based modelling for many applications including industrial water and wastewater treatments and food industries. ANN consists of various structures and learning algorithm, which indicates the type of the neural network. Among popular basic structures employed by researchers are feedforward neural network (FFNN), recurrent neural network, and radial basis function neural network (RBFNN). Examples of the learning algorithms available to map the input to desired output tune the weights of neurons such as back propagation, gradient-based, levenberg-marquardt (LM) and many others. ANN are strongly interconnected systems of so-called neurons (contain input and output) which have simple behavior but when connected they can solve complex problems. Several activation functions are available to evaluate neuron output. Among the popular functions are the linear function, hyperbolic tangent function, and sigmoid function [42]. Better prediction by the ANN structure can be obtained using soft computing optimization, particularly when dealing with more complicated system like fouling behavior.

ANN is the most popular algorithm for modelling of membrane filtration system compared with other soft computing techniques. Previous research discussed in [43] in mid 90's is the pioneer of ANN application in membrane filtration systems. In their work, the prediction of hydraulic resistance for cross flow MBR is performed. Three inputs of the ANN applied, which are cross flow velocity, TMP and filtration time. Another work for resistance prediction using ANN models is also performed by Delgrange et al. [29] for UF membrane filtration system. The aim is to predict the total resistance after each filtration cycle ended. The parameters included temperature, turbidity, permeate flow rate, and resistance at the filtration start and before the previous backwash. Work by Bowen et al. [44] predicts the colloid dispersion charged from UF membrane filtration system using backpropagation neural network (BPNN) model. This work uses pH, ionic strength, TMP and filtration time as inputs to the BPNN model and the results showed reasonable predictions of the flux charged from the system. The same data was utilized by Vivier and Mehablia [45] and Wei et al. [46] to improve the basic BPNN and multiple regression models using wavelet neural network. The proposed method shows better results regarding convergent time and accuracy and it is suitable to be used for modelling cross flow permeate model.

ANN model was utilized in [47] to model sludge characteristics in the SMBR for synthetic wastewater treatment. Authors claim that with the BPNN model, the online control can be achieved for the process. This structure consists of five inputs, four hidden nodes and three outputs. List of the input parameters are utilization associated product, soluble microbial product (SMP), biomass associated product, MLSS and temperature, while the outputs are MLSS effluent and critical flux. The implementation of recurrent ANN has been demonstrated by Hamachi et al. [12] to predict the permeate flux and deposit thickness for crossflow membrane filtration. Process variables such as TMP, crossflow velocity and concentration of the colloidal suspension are used as ANN inputs. The starting point values for permeate flux and deposit thickness fitted back to the ANN. Application of neural network also can be found in [48] in the prediction of flux decline during phosphate removal using MBR. The authors compared two neural network models with that of Koltuniewicz's method. The first neural network uses time, TMP, fly ash and phosphate concentrations as its inputs and the second-model added another input which is the type of membrane. The output of both models is the permeate flux. The results showed that ANN models are preferable to Koltuniewicz's method. Another UF membrane filtration system has been presented by Curcio et al. [49] to model the flux decline under pulsating conditions. Data from three different filtration operation times (60, 90, and 120 s) with fixed pulse duration or relaxation time (10 s). The inputs of FFNN model are filtration operation time, sampling time and inlet flow rate, while permeate flux is the output of the network.

The work by Shetty and Chellam [50] demonstrates the use of LM training algorithm in FFNN model to predict the total resistance in membrane filtration for drinking water system application. The variables of the model input are time, influent flow rate, pH, total dissolved solid (TDS) and ultraviolet absorbance, permeate flux and TMP. The model can be used for short and long filtration predictions. In [51], flux filtration prediction under various feed suspensions at different hydrodynamic parameters was investigated. This prediction considers feed concentration, initial permeate flux, entrance shear rate, instantaneous TMP and filtration time as input parameters to the neural network model for poly-dispersed feed suspensions in the crossflow membrane filtration. The effect of TMP on the operation parameters and influent quality was modelled using BPNN in [52] for ceramic membrane filtration process. Various relevant parameters used in the model training procedure. The TMP start and end cycle with different influent parameters and operations were used to predict the TMP next cycle. The overall structure is very complex. However, the prediction is very reliable and can be used to replicate the real system efficiently. The ANN model that represented the backwash effect to the permeate flux has been discussed by Aidan et al. [53]. Several backwash intervals have been tested to the flat sheet filtration. The multilayer neural network is used to model the system with backwashed interval and filtration interval used as an input to the model, while flux is the output of the model.

Various activation functions and ANN structures were tested by Kabsch-Korbutowicz and Kutylowska [54] in the modelling of detergent wastewater treatment using UF membrane filtration. The inputs of the ANN are temperature, recirculation flow and inlet-outlet pressure. The best network was found using four input neurons, eight hidden neurons and one output neuron with hyperbolic tangent and sine function of activation and quasi-Newton method of training algorithm. In [23], total hydraulic resistance and dynamic permeate flux were modelled using a multilayer perceptron feed-forward neural network (MLP-FFNN) for NF treatment of regeneration waste brine. The network structure was developed using three input layers, one hidden layer and two output layers with sigmoid activation function. Time, TMP and temperature are the input parameters of the model. The simulation result showed the TMP is the main influent parameters of the model and this is further verified by the sensitivity test conducted during the experiment work.

The application of the membrane filtration system in food industries also employed ANN modelling technique to predict fouling mechanism. The work in [55] has proven the ability of ANN with LM training algorithm to predict the fouling for milk filtration in UF cross flow filtration. This work also considers the sequence cycle and cleaning protocol with different agents in the developed model, specifically in the operational cycle where the aggressive cleaning, the filtration time and the permeate flux are the predicted outputs. The best result was attained at five hidden neurons with back propagation LM training algorithm. Another ANN modelling of milk filtration process during cross flow UF membrane was demonstrated in [13]. Two networks are developed in this process. The first network consists of two inputs (TMP and filtration time) and two outputs (permeate flux and hydraulic resistance). The second network predicts rejection materials from the process which are protein, fat, lactose, ash and total solids while maintaining the same inputs with that of the first network structure. The authors reported that a single hidden layer is sufficient for both networks to give the satisfactory prediction of the outputs. ANN model also was successfully used and optimized by Nourbakhsh et al. [56] for red plum juice permeate flux prediction under the cross-flow filtration. The input parameters for this model were TMP, feed temperature, the cross-flow velocity of feed and pore size of the membrane for filtration. In their work, response surface methodology (RSM) which is one of the optimization methods was used to optimize the ANN structure regarding a number of neurons training epoch, step size, training percentage and momentum coefficient. The work by Eberhart and Kennedy [57] presented ANN model for effluent quality of the SMBR treating cheese whey wastewater, with the inputs are COD, ammonia, nitrate and total phosphate concentrations. The results show that the ANN provide good agreement for modelling of this effluent. The work by Ren et al [58] focuses on the effects of operational parameters on effluent quality of a SMBR for high-strength traditional Chinese medicine wastewater using BPNN.

Using simulation model, the authors found the optimum parameters of the process. Four inputs and three outputs were used in training the network which are MLSS, COD loading rate, SRT and HRT for the input parameters, while COD filtrate, mix and rejection are the output parameters. The result showed the BPNN model accurately follows the trend of the COD model.

Oil refinery wastewater treatment is another venture of membrane filtration process. This process usually includes the biological process before the filtration takes place. The application of nonlinear approach like ANN is of highly demanded in this situation. Filtration model developed in [14] employed FFNN training with LM algorithm applied in commercial crossflow polyacrylonitrile UF MBR filtration for an oily condition of wastewater treatment. The investigation involves the model development for fouling resistance and permeates flux. Another ANN application for prediction performance of oily wastewater treatment is found in [22], where the researchers modelled the quality of membrane sequencing bioreactor process under UF membrane filtration system. The inputs are time, variations of organic loading rate, retention time and TDS. The outputs are COD, MLSS, total organic carbon and oil in the sludge. Mean square error and R^2 were used to measure the accuracy performance of the neural network that was trained using GA.

Geissler et al. [15] developed two models which are the semi-empirical model and ANN-based model for permeate flux modelling in the capillary based SMBR. The ANN model is based on the Elman neural network structure. The inputs to the ANN are TMP, the rate of TMP change, TMP during backwash, filtration cycle length, backwash cycle length, SRT, TSS, temperature and oxygen decay rate. The ANN provides good accuracy with small error compared to the semi-empirical. Submerged membrane flocculation hybrid systems for synthetic wastewater treatment filtration model were also developed by Erdei et al. [59] using different types of neural network structures. Three nonparametric ANN models which are multi-layer perceptron neural network (MLPNN), RBFNN and general regression neural network were compared with parametric multivariate nonlinear models. The inputs of the model are coagulation dose and filtration time, while the outputs are the TMP, permeate pH and permeate. The ANN models provide good prediction of the TMP profiles during the filtration process compared to the multivariate nonlinear models.

The development of knowledge-based system has been performed by Comas et al. [60]. This work described the knowledge-based decision support system module to regulate the air flow rate of an MBR with variable flux and demonstrated the usefulness of the approach. Another work on the application of knowledge-based system can be found in [61] on the integrated of operation and remote control of the biological and physical processes of MBR for air-scour consumption automation and energy consumption minimisation. The key operational variables included permeate flux, relaxation and backwash times, backwash flows and times, aeration flow rates, chemical cleaning frequency, waste sludge flow rate and recycle flow rates.

As an alternative version of modelling approach, simple time series like autoregressive, state-space and subspace formulations developed from system identification procedures can be formulated for an advanced control system [62]. For instance, the time series input-output modelling approach has been performed by Paul [63] using full scale side stream MBR. The implementation of time series models involved predicting extra-cellular polymeric substance and SMP levels for an industrial wash water from a salad processing factory. In comparison, the subspace and auto-regressive eXogenous input formulated biological models were reasonably accurate when compared to the standard biological ASMs. However, these time series models require a much longer historical data set.

The neural network is also applied in RO membrane applications. A previous work by Khayet et al. [64] demonstrates the application of ANN in modelling of salt rejection, flux and performance index using sodium chloride concentration in feed solution, feed temperature, feed flow-rate, and operating hydrostatic pressure. The result was compared with RSM and showed that the optimal conditions offered by ANN are better than those given by RSM. From [64] it can be observed from both methods, that the ANN approach is more flexible whereby it requires no standard experimental design and allow for an additional of new experimental data to build the model.

The application of ANN is also used in prediction of permeate TDS, and permeate flow rate for seawater RO plant [65]. In the network development, time, feed temperature, feed TDS, TMP, and feed flow rate were used as input parameters with three layers network and five neurons. From the results, the ANN model can be used to predict long-term filtration performance of seawater RO filtration system with good accuracy. The application FFNN algorithm was used by Abbas and Al-Bastaki [66] in membrane RO system for sea and brackish waters desalination. Variations of water feed pressure, temperature and salt concentration are used to predict the water permeate rate in the network structure. LM training algorithm was employed in the ANN training procedure and the performance of system was assessed using root mean square error and R^2 performance indexes. NF/RO system was modelled by Zhao et al. [67] using MLPNN and RBFNN. The research predicted permeate stream of TDS in the filtration system. The ANN prediction models were compared with the modified and conventional methods. The authors are satisfied with the ANN performance, which gives good prediction for inputs changes. Another NF/RO modelling has been implemented in [68] using bootstrap aggregated neural networks and showed it superiority when compared to single neural network and multiple linear regressions.

3.2. Other artificial intelligent-based modelling

Fuzzy logic model is another nonlinear modelling that is widely applied in many chemical processes. The most pertinent feature of fuzzy logic for which it receives so much attention is its scope of partial matching. In the membrane filtration process, fuzzy model was proposed by Rahmanian et al. [69] to model lead removal using micellar-enhanced ultrafiltration (MEUF). The result shows acceptable membrane permeates flux prediction. The used of hierarchical fuzzy approach developed by Madaeni et al. [70] is employed in the GA and sequential quadratic programming to optimize the fuzzy parameters of milk filtration process. VolateFat (Fattvolatile fatty acids), time, pressure, temperature and velocity are the inputs of the fuzzy model while permeate flux is the target output. The optimization of the fuzzy parameters improves the prediction capability of the model. Another flux decline using fuzzy model was studied by Ikonić et al. [71] to model cross flow MF membrane. The TMP, flow rate and suspension concentration are used as an inputs model. The mamdani type of membership function used in the research shows a good performance for predicting flux decline in the filtration system. Prediction of specific permeate flux during crossflow MF of polydispersed colloidal suspensions were discussed by Altunkaynak and Chellam [72]. A combination of feed suspension and hydrodynamic properties of crossflow MF system is also explored. Beside permeate flux model, the fuzzy algorithm with ANN was also employed to model chemical cleaning performance of MF membrane filtration. The research shows that the cleaning agent type, cleaner concentration, temperature, cross-flow velocity and time can be used to predict cleaning performance and flux recovery of the filtration system.

ANFIS is a combination of neural network and fuzzy logic reasoning. It is an effective modelling method that can provide good model approximation, particularly for highly non-linear systems. sugeno type of fuzzy interface system is commonly used in ANFIS modelling. The neural network is used to estimate and optimize the membership function. The learning or training process will determine an optimum premise and consequence parameters. The details of the learning procedure can be found in [73]. ANFIS has shown its capability to model complex systems in many application such as in [74–76]. In membrane filtration process, ANFIS is among the common method used for modelling the system. The work by Rahmanian et al. [77] used ANFIS to predict the permeate flux and rejection rate for cross flow MEUF process. The inputs such as pH, molar ratio and concentration were utilized in prediction the separation process. The ANFIS was compared to the ANN model and it shows that the former model is more reliable with respect to the accuracy of the filtration model. Another application of ANFIS model was found in [78] where this model is applied to investigate the prediction performance of plate and frame membrane filtration of waste water treatment. Flow rate, temperature, pH and concentration are the input parameters of the model, while the outputs are permeate flux and COD rejection rate. In addition, ANFIS performs well in modelling of permeate flux in cross flow UF membrane for oily wastewater, where the input parameters are cross flow velocity, TMP, time and temperature while the permeate flux is the output the model [79]. For the same application of oily wastewater [80], ANFIS has shown reliable prediction of the permeate flux with different inputs (cooperative free volume, temperature, TMP, pH and filtration time).

3.3. Soft computing optimization methods

One of the most difficult tasks in the design of ANNs is choosing proper internal network parameters and appropriate network geometry, which basically determined by trial and error method. Back-propagation is one of the most commonly used algorithms to train the ANN. However, several problems highlighted by researchers with the BP algorithm such as low convergent speed and easy to trap in local minima [81,82]. The gradient-based technique that employed in the BP algorithm is much dependent on the initial value of the weights and biases. This algorithm also depends on the value of training parameter such as learning, momentum rate and epoch which is determined by trial and error [61].

Soft computing optimization is a way forward in improving the ANN learning or training process. GA is one of the pioneer heuristic soft computing optimization methods for neural network training and the most often used in membrane filtration systems. In general application, the work by Gupta and Sexton [82] presented better results of training the FFNN using GA than the traditional techniques of backpropagation. For specific membrane applications, Behari and Ray [83] proposed a GA to determine the optimal design networks in BPNN and RBFNN using GAs. The performance efficiency of predicting flux decline in crossflow membrane reported by Behari and Ray is improved. More studies in membrane filtration applications are available for the use of GA-ANN that aimed for prediction performance efficiency such that; increase flux efficiency during cross flow MF of particulate suspension by Liu et al. [84], increase cleaning performance of MF membrane filtration by Madaeni et al. [85], minimizing the membrane fouling in UF MBR for oily wastewater while achieving maximum operational setting with multi objective function GA by Soleimani et al. [14], improve prediction performance of oily wastewater treatment using UF membrane by Pendashteh et al. [22]. These works of GA-ANN provide minimum prediction errors indicating an improvement of prediction performance efficiency by GA-ANN. The GA-ANN is also successfully employed in optimizing RO water treatment application to obtain minimum permeate conductivity [86]. In addition, the GA is used in the experimental study of UF membrane filtration of refinery effluents to obtain optimal parameters for least square support vector machine filtration model [87]. Recent improvement of hybrid GA-ANN based on evolutionary approach also discussed in [88] for the enhanced polymer UF membrane process.

Apart of improving prediction performance efficiency in membrane filtration, the combination of neural network with GAs can provide fast process optimization and reduced cost of operations as presented by Strugholtz et al. [89] using ceramic MF membrane in the application of drinking water treatment. The simulation work by Ludwig et al. [90] applied the GA for achieving optimal filtration to relaxation ratio using the integrated biological ASM1 model and MF membrane. The optimum filtration and relaxation obtained from the optimized parameters able to reduce the operational cost in terms of cleaning and maintenance. The GA algorithm was found to be very effective with fast convergent time. The work by Chen and Seidel [91] determine the optimal operating condition of NF with fouling by natural organic matter using GA optimization, whereby the optimization of the cost function represents the operating cost of running the membrane plant. Overall, works presented in [89–91] showed the minimization of operational costs with a cost reduction of about 15%–30%.

Another heuristic soft computing optimization schemes that getting more attention in solving many optimization problems are PSO and GSA. The PSO algorithm is inspired by behaviour of a group of animals hunting and is very effective in finding an optimal solution. It is fast and very reliable in searching for minimization. The PSO algorithm has been employed for the training of neural network in many applications including membrane fouling [91–95]. The work by Yusuf et al. [95] has proven the capability of using PSO-ANN to model the dynamic behaviour of the filtration process. For GSA algorithm, it is inspired by a gravitational theory in space that attracted to each other and this algorithm is good in optimizing the network structure [96,97]. However, GSA has a problem with slow searching speed and no recovery on the premature convergent [98]. Works on the improvement of GSA algorithm can be found in [99–101]. Among the main highlight of the GSA improvement is on its hybrid approach and the combination of the hybrid GSA with other heuristic algorithms. The work by Mirjalili et al. [92] investigates the application of hybrid PSO and GSA (PSOGSA) using low-level co-evolutionary heterogeneous hybrid to train the FFNN. The hybrid method in [92] relatively give better solution compared with the PSO and the GSA individually. Khadanga and Satapathy [102] developed a hybrid GSA with GA algorithm to improve the fundamental of GSA technique. In this work, the authors applied the algorithm to tune the controller damping in a power system application. The combination of social thinking ability of PSO and the explorative

Table 3
Summary of soft computing applications in membrane filtration systems

Author/s	Applications in membrane filtration systems
Dornier et al. [43]	BPNN to predict hydraulic resistance for cross flow MF MBR
Delgrange et al. [29]	BPNN to predict total resistance for UF membrane
Hamachi et al. [12]	Recurrent ANN to predict the permeate flux and deposit thickness for crossflow membrane
Chen and Seidel [91]	ANN-GA for predicting and optimizing NF membrane system performance
Shetty and Chellam [50]	LM training algorithm in FFNN model to predict the total resistance in NF membrane
Chen et al. [58]	BPNN for the effects of operational parameters on effluent quality of a SMBR
Behari and Ray [83]	GA to search the optimal geometry and values of internal parameter of a BPNN and RBFNN to predict flux decline in crossflow membrane
Aidan et al. [53]	Multilayer neural network for backwash effect to the permeate flux in the flat sheet filtration
Strugholtz et al. [89]	BPNN - GA to predict the effect of TMP for ceramic membrane filtration
Lee et al. [65]	FFNN for optimizing operation of a seawater RO plant
Wei et al. [46]	Wavelet neural network for cross flow UF MBR
Kabsch-Korbutowicz and Kutylowska [54]	Hyperbolic tangent and sine function of activation and Quasi-Newton method of ANN training algorithm for UF membrane
Erdei et al. [59]	Multivariate nonlinear model vs. ANN models (MLPNN, RBFNN, GRNN) for submerged membrane flocculation hybrid systems
Comas et al. [60]	Knowledge-based- decision support system to regulate the air flow rate of an MBR
Khayet et al. [64]	ANN vs. RSM for RO membrane
Rahmanian et al. [69]	Fuzzy model for lead removal of MEUF
Gholikandi and Khosravi [47]	BPNN for online control of critical flux in SMBR
Madaeni et al. [85]	ANN, fuzzy logic models and GA for chemical cleaning of MF membranes
Rahmanian et al. [77]	ANFIS to predict the permeate flux and rejection rate for cross flow MEUF
Madaeni et al. [70]	Hierarchical fuzzy approach for flux prediction with GA and SQP optimization
Fazeli et al. [87]	Hybrid Intelligent Approach (Least-squares support vector machine with GA) for modeling of UF Refinery Effluents
Nourbakhsh et al. [56]	RSM to optimize the ANN structure to predict the permeate flux in crossflow membrane
Chew et al. [27]	Hybrid modelling (ANN-Darcy's law) to represent the dead-end UF process
Avarzaman et al. [30]	Intelligent modelling using fuzzy inference system approach for permeate flux during membrane clarification of pomegranate juice
Sekulic et al. [31]	ANN for complexation- microfiltration process
Khaouane et al. [68]	BANN for NF/RO modelling has been implemented in [68] using Bootstrap Aggregated Neural Networks (BANN)
Yusuf et al. [95]	PSO-ANN for filtration modeling in SMBR
Dasgupta et al. [88]	Hybrid GA-ANN based evolutionary approach for the enhanced polymer UF membrane process

capability of GSA was further investigated in [103] and indicated better explorative capability when applied to beam pattern optimization in collaborative beam forming. In [104], a new PSOGSA was developed using cooperative approach for the application of economic emission load dispatch. In this approach, the velocity update equations of GSA and PSO are combined as a main velocity update equation. The coefficients of the velocity update equation are designed to select either using individually (PSO or GSA) or using the hybrid velocity update equation. However, there is no interaction between each of the algorithms which the evolvement of the algorithm still within whole group. The possibility of the of the algorithm trap in the local optima still high, where this matter can be reduced using multi groups with different algorithms working together searching for the best solution. Therefore, it is important to further investigate the possibility of the hybrid soft computing optimization approach in the modelling and prediction of membrane filtration systems, particularly for the training of ANN. Table 3 provides state-of-the-art applications of soft computing in membrane processes.

4. Conclusion

Modelling has become an essential procedure in many process industries including membrane filtration process applications. This procedure enables the processes to have an earlier prediction either for monitoring purpose or control applications in future. Model accuracy is crucial to ensure the best possible prediction of actual processes, and the most important is reliable. For a highly complex and non-linear dynamic of membrane filtration system due to fouling behaviour, finding the accurate models could be challenging. Therefore, this paper reviews the available modelling and prediction of membrane filtration systems using soft computing techniques. The application of soft computing techniques in modelling of membrane filtration system is still limited. Most of the applications were implemented into cross flow type of filtration system, which is for the purpose of monitoring only. The review also highlighted on the problem arises in the membrane filtration process which is the blockage of the membrane or so-called fouling phenomena. Fouling causes the membrane filtration process become more complicated and difficult to model. In addition, the existing models focused on the membrane filtration effluent quality rather than filtration performance. Therefore, the review focuses on the selection of parameters affecting membrane fouling prior to modelling and control of membrane filtration systems for the purpose of filtration performance. Factors affecting fouling behaviour are also discussed and analysed. For specific control system design of membrane filtration for instance, simple time series model can be appropriated to evaluate the filtration performance. However, to deal with complex behaviour of fouling in predicting the filtration output, the soft computing procedure is needed, particularly for parameter estimation.

ANN is the most popular AI-based soft computing technique used in modelling of membrane filtration system. Other techniques such as fuzzy, knowledge-based systems and ANFIS models are also applied in the membrane filtration systems and provide acceptable modelling results in most of the applications. The ANN model is chosen due to its less complexity and involved less tuning of the process parameters. When using ANN modelling, an optimal weight and bias combination is critical in order to obtain the desired output prediction during the training procedure. This can be solved using several training algorithms available such as LM, resilient back-propagation and gradient decent methods. With the capability of soft computing techniques in prediction of membrane filtration process, it can be easily used for controlling the filtration process and thereby eventually develop energy saving control strategy in the filtration process. Optimal operation settings like backwash, aeration bubble shear force and relaxation were shown to be a significant cost factor that is sensitive to operating conditions and becomes of priority target for the optimization.

In the literature, most of the filtration systems employ the classical ANN modelling without external optimizations. In this review also, the application of soft computing optimization techniques (as external optimizations) that mostly applied in membrane filtration systems is revealed and discussed. The application of optimization technique is related to the optimization of the influent parameters such as feed concentration, pH and filtration operation parameter like a TMP measurement. From literature, the GA has been widely used in the membrane filtration modelling to assist on model parameters selection and structure selection. Other optimization techniques such as PSO, GSA and the hybrid optimization can be considered further as an alternative way of improvement, especially when dealing with complex behaviour like fouling. The optimization techniques and their hybrid approaches have proven their capability to obtain global solution for many applications and hence, may give better assistance in optimizing the membrane filtration system in term of operation optimization and model parameters selection.

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