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Advanced process control for ultrafiltration membrane water treatment system

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ABSTRACT

Dead-end ultrafiltration (UF) has been considered as a more energy efficient operation mode compared to cross-flow filtration for the production of drinking/potable water in large-scale water treatment systems. Conventional control systems utilize pre-determined set-points for filtration and backwash durations of the constant flux dead-end UF process. Commonly known potential membrane fouling parameters such as feed water solids concentrations and specific cake resistance during filtration were not taken into considerations in the conventional control systems. In this research, artificial neural networks (ANN) predictive model and controllers were utilized for the process control of the UF process. An UF experimental system has been developed to conduct experiments and compare efficiencies of both the conventional set-points and ANN control systems. The novelty of this study is to utilize commonly available on-line and simple laboratory analysis data to estimate potential membrane fouling parameters and subsequently utilize the ANN control system to reduce water losses. Reduction of water losses were achieved by prolonging filtration duration for feed water with low turbidity using the ANN control system. This advanced control system would be of interest to operators of industrial-scale UF membrane water treatment plants for the reduction of water losses with existing facilities.

1. Introduction

Proliferation of human population and rapid development on a global scale has pushed towards higher consumption and quality of drinking/potable water particularly in urban cities (Goh et al., 2016). Developed Asian countries such as Singapore, Japan and South Korea have all adopted large-scale ultrafiltration (UF) membrane water treatment systems to partially fulfil their nations need for potable water through public-piped water supply and distribution networks. Membrane technologies have been reported to fulfil multiple sustainability criteria in terms of flexibility, adaptability, minimal foot print and environmental impacts (Le and Nunes, 2016). UF membrane systems have gained immense attention in water treatment industry as it could provide consistent filtrate quality by removing colloids, particles and microorganisms (Monnot et al., 2016). Most of the large-scale UF membrane water treatment plants are operating under constant flux dead-end filtration mode with intermittent backwash sequence to reduce the energy consumption per cubic meter of filtrate (Massé et al., 2011). High energy consumption is directly related to carbon emission which causes environmental issues (Rahim and Raman, 2015). Polymeric membranes particularly Polyethersulfone (PES) and Polyvinylidene fluoride (PVDF) are dominantly utilized at industrial-scale UF membrane water treatment plants (Hög et al., 2015). PES membranes exhibit beneficial properties such as good thermal stability, excellent chemical resistance and wide pH tolerance. This type of membranes have the potential to be blended with additives to reduce membrane fouling tendency (Vatsha et al., 2014).

Membrane fouling remains the most critical issue for commercial systems (Smith et al., 2006; Guo et al., 2012). Many approaches to minimize membrane fouling have been proposed such as membrane surface modification, physical and hydrodynamic cleaning methods to enable better removal of attached solids on membrane surfaces (Shamsuddin et al., 2015). Membrane cleaning

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is defined as procedures applied on the membrane to relieve it of non-integral substances which are known as "foulant" (Porcelli and Judd, 2010). Physical cleaning method such as hydraulic backwash is essential for the sustainable application of UF systems in water treatment processes. The extent of irreversible fouling is highly dependence on the hydraulic cleaning efficiency (Chang et al., 2015). Intermittent backwash after each filtration sequence is commonly conducted as physical cleaning in dead-end membrane filtration systems to recover membrane permeability (Mendret et al., 2009). Membrane fouling could be mitigated by optimization of the operational conditions (Shi et al., 2014).

Natural surface water from rivers are common sources of feed water to industrial-scale water treatment plants to produce potable water (Davies and Mazumder, 2003). It contains matrix of organic matters and particles which are considered to be the main sources of organic foulant on UF membranes (Shang et al., 2015). Feed water characteristics and operational conditions of UF membrane processes are factors which affect the systems performance (Decarolis et al., 2001). Any characteristics or composition changes in the feed water could induce huge changes on membrane fouling (Massé et al., 2015). Most industrial-scale water treatment plants analyse and monitor parameter such as raw water turbidity on hourly basis to detect any possible feed water characteristic changes. Recent literature has suggested that specific cake resistance or α is one of the important parameter for estimation of potential membrane fouling propensity (Sioutopoulos and Karabelas, 2016). It is a commonly used parameter to express the characteristics of the cake layer. Most industrial-scale UF membrane water treatment plants do not have the advanced analysis equipment and skilled-personnel required to determine α experimentally at their own in-house laboratories.

The dominant fouling mechanism in dead-end filtration for physical solid-liquid separation of UF process is known as "cake" formation which could be described by Darcy's equation (Sioutopoulos and Karabelas, 2015). Feed water characteristics such as solids concentrations and specific cake resistance are some essential parameters in Darcy's equation. Constant changes of surface water characteristics due to heavy rainfalls and surface run-off cause these parameters to fluctuate from time to time. Under constant flux dead-end filtration operation mode, the trans-membrane pressure (TMP) readings increase gradually over time due to cake formation on the membrane surface (Iritani et al., 2015). High TMP during operation is considered undesirable as more energy is required for the filtration process.

Conventional set-points control systems for industrial-scale UF membrane water treatment plants utilize a pre-determined filtration duration before an intermittent backwash is initiated (Cogan and Chellam, 2014). Programmable logic controllers (PLC) are often programmed with user's defined set-points to perform the control loop automatically (Alphonsus and Abdullah, 2016). Some of the most common causes of membrane fouling are related to its process control and operation parameters (Damour et al., 2014). Feed water characteristic such as turbidity is one of the major parameter often monitored on hourly basis during operation. The feed water characteristics and the complex interaction of the contaminants with the membrane necessitates formulating and solving highly non-linear equations or theoretical models (Shetty et al., 2003). In accordance to Darcy's equation, the solids contaminants build-up on the membrane surface increases the TMP during constant flux dead-end filtration (Mendret et al., 2009). However, the rate of TMP increase is governed by feed water characteristics which may differ from time to time if the source is from natural rivers.

Artificial neural networks (ANN) provide an alternative method to model these complex systems based on commonly available data (Hussain and Kershenbaum, 2000; Shetty and Chellam, 2003; Chew et al., 2017). Successful applications of ANN in chemical systems as models and estimators have been reported in literature (Mohd Ali et al., 2015a; Mohd Ali et al., 2015b). ANN control system has been utilized in the steel pickling process which involved the release of hazardous wastewater with major environmental impacts (Kittisupakorn et al., 2009). In another research study, ANN based correlation was used to estimate the permeability constant of membrane systems under fouling conditions (Barello et al., 2014).

Fouling mitigation and water losses reduction control methodology for membrane processes are research areas which have generated immense interests. Aluminium coagulation has been reported as an effective control measure to reduce UF membrane fouling from organic matters (Yan et al., 2017). An advanced fouling control method which utilizes pulsed short-wavelength ultraviolet light with pre-coagulation to mitigate membrane fouling by micro-organism was also highlighted in literature (Yu et al., 2016). In another different approach, a real-time control system using self-adaptive cycle-to-cycle has been utilized to control the dosing rate of coagulant prior to the UF process (Gao et al., 2017). This control strategy has been found to be very robust to ensure fouling control measured in an UF system. All of the control methods mentioned earlier required the use of coagulant or additional advanced equipment for implementations. Limited and very few research studies have reported using commonly available on-line and simple laboratory analysis data to increase the efficiency of direct feed UF systems by reducing water losses while ensuring acceptable potential membrane fouling propensity.

A typical direct feed industrial-scale UF membrane water treatment system consists of various control valves, pumps, pressure transmitters, storage tanks and flowmeters to implement the conventional set-points control system. Raw water from rivers are usually used as feed water to the UF system. During the filtration sequence, a feed pump is utilized to provide sufficient pressure and flow rate into the UF membrane modules for the solid-liquid separation process. Filtrate from the UF membrane modules are temporary stored in a filtrate tank before transferring to a contact tank for chlorine disinfection. During backwash sequence, water from the filtrate tank is pumped back in reverse flow to the UF membrane modules to dislodge accumulated solids and foulant. Fig. 1 shows the schematic diagram of a direct feed industrial-scale UF membrane water treatment system. Under the conventional set-points control system, both the filtration and backwash sequences operate on alternate basis to produce the desired volume of filtrate while ensuring periodic cleaning of the membrane to reduce fouling.

In this research study, an advanced control system utilizing ANN model and controllers have been implemented on an UF experimental system operating under constant flux dead-end filtration mode. Natural surface water from a river was directly fed to the UF experimental system. It contains significant amount of suspended solids which could cause membrane fouling. Correlation of the feed water turbidity and its solids concentrations were established using simple laboratory analysis procedures. The ANN control system predicts the specific cake resistance using relevant inputs data during the filtration sequence. Potential membrane fouling propensity estimated from these data was utilized by the ANN control system to regulate the filtration durations. Instead of depending on advanced analysis equipment to determine the potential membrane fouling propensity, commonly available on-line and simple laboratory analysis data were utilized in the ANN control system. This approach brings down the capital expenditure required to upgrade available facilities in commercial UF membrane water treatment plants to reduce water losses under fluctuating feed water characteristics. Comparisons between both the conventional

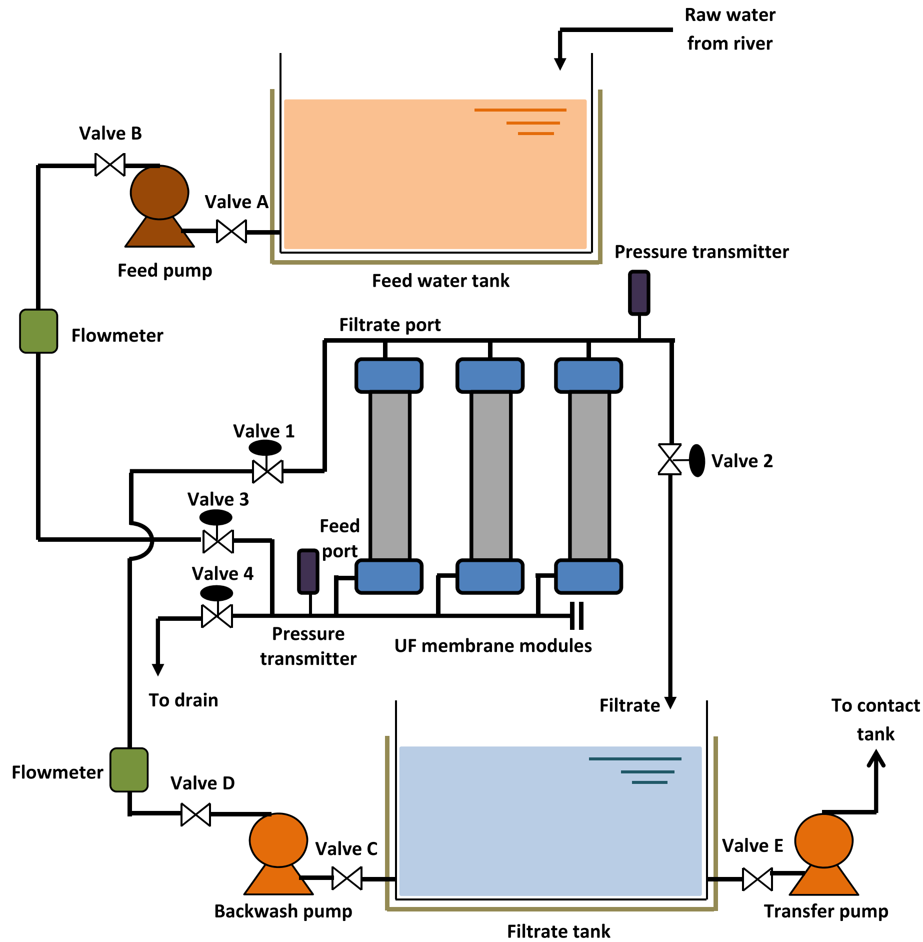


Fig. 1. A typical direct feed industrial-scale UF membrane water treatment system.

set-points and ANN control systems have been conducted to elucidate the advantages and drawbacks of both systems.

2. Methodology

On-line data collection was required to train the ANN model and controllers for the UF process. An UF experimental system has been designed and commissioned to gather related data and implement the on-line process control systems automatically. This experimental system was equipped with UF membrane module Dizzer P 2521–1.0 manufactured by Inge GmbH, Germany. The UF membrane was made from modified PES material with 1.0 m^2 of membrane surface area suitable for constant flux dead-end filtration operation mode. Fig. 2 shows the actual and schematic diagram of the UF experimental system. Control valves labelled in Fig. 2 as “Valve 1A”, “Valve 2A”, “Valve 3A” and “Valve 4A” correlate with the control valves labelled as “Valve 1”, “Valve 2”, “Valve 3” and “Valve 4” for the industrial-scale UF membrane water treatment system in Fig. 1. During filtration sequence “Valve 2A” and “Valve 3A” is opened to allow the feed water flow into the UF membrane module. The flow of water (filtrate) into the UF membrane module is reversed during the backwash sequence by opening “Valve 1A” and “Valve 4A”.

The supervisory control and data acquisition (SCADA) of the UF experimental system consists of a control panel linked to personal computer. This SCADA system utilized MATLAB software to implement on-line process control. The process sequence of the UF experimental system was very similar to an industrial-scale UF membrane water treatment plant operating under constant flux dead-end filtration mode (Chew et al., 2015, 2016). Same river water source used as feed water to the industrial-scale UF membrane water treatment plant was utilized as feed water to the UF experimental system. The UF membrane module for all the experiments was also produced by the same membrane manufacturer of the UF membrane water treatment plant.

During the experiments, TMP readings (pressure difference between the UF membrane module feed port and filtrate port) from the pressure transmitters were continuously monitored and recorded by the SCADA system. The feed water turbidity was analysed using laboratory turbidity analyser and entered into the SCADA system prior to the experiments. In this study, constant flux was considered to be achieved within a tolerance of ±10% from the desired flux rate. Manual volumetric analyses during the experiments were conducted to ensure the flux rate was within this tolerance. All the on-line readings and status of the control valves and pumps could be viewed from the graphical user's interface of the SCADA system during the experiments. The SIMULINK toolbox control diagram under the MATLAB software for the UF experimental system is shown in Fig. 3.

The SCADA hardware communication system consists of 2 inputs (feed and filtrate ports pressure transmitters) and 6 outputs (four control valves and two pumps) to implement automatic process control on the UF experimental system. All relevant data such as on-line TMP, filtration time, backwash time, control valves and pumps status were recorded digitally in the SCADA system for post analysis. This automation process enabled different control

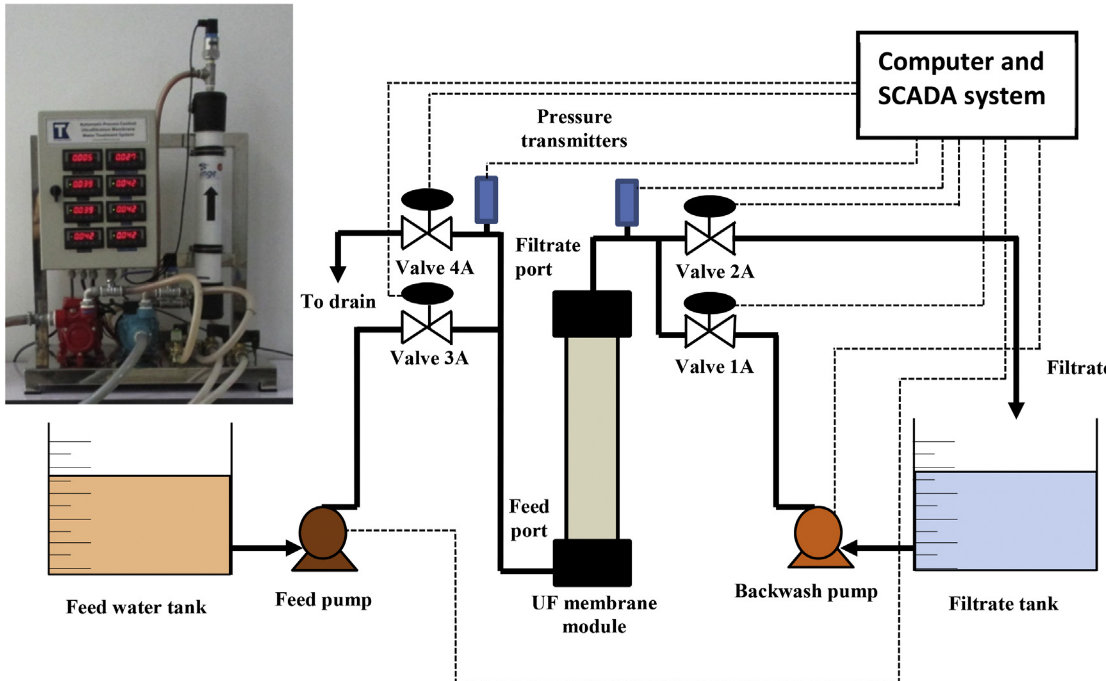


Fig. 2. Actual (inset) and schematic diagram of the UF experimental system.

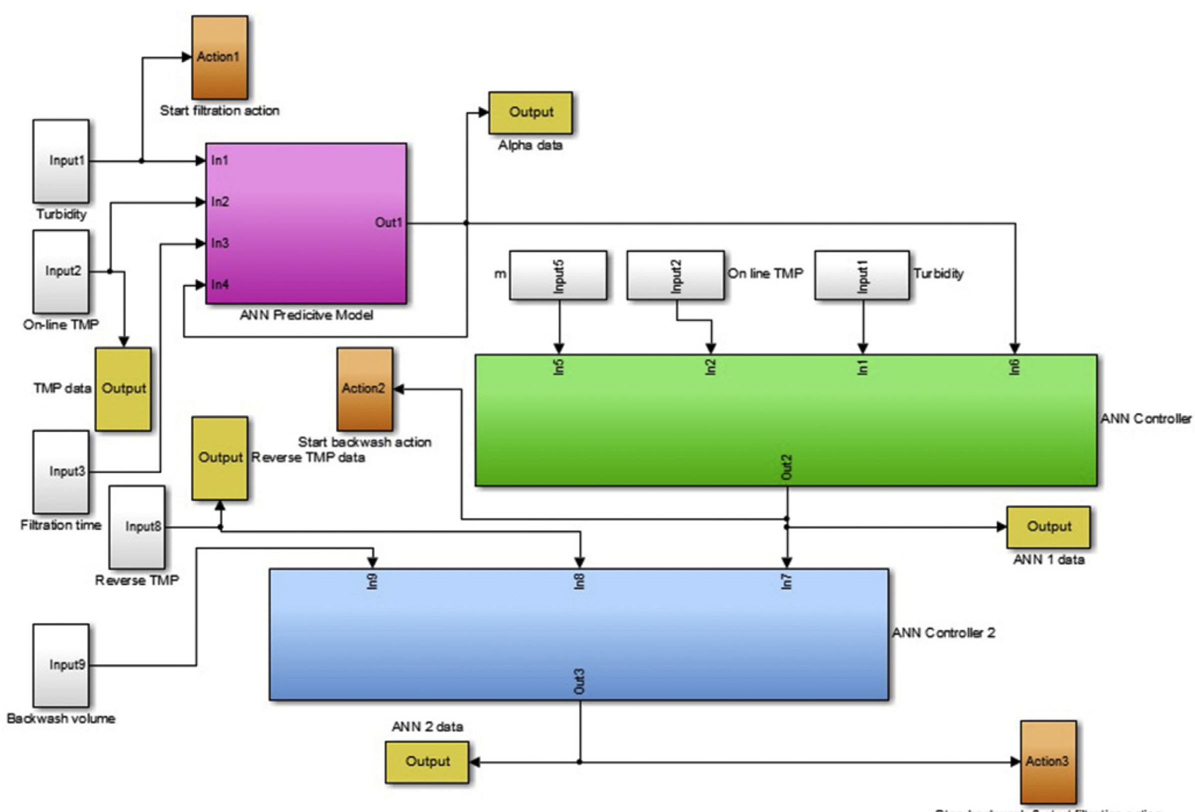


Fig. 3. MATLAB software control diagram for the UF experimental system.

systems to be implemented on-line to compare their performances with various feed water samples.

2.1. Conventional set-points control system for UF process

Typical industrial-scale UF membrane water treatment plants commonly utilize conventional set-points control systems for the automation process operation. There are two major sequences in the constant flux dead-end membrane filtration process which are known as filtration sequence and backwash sequence. Before the process commences, pre-determined filtration duration (normally between 20 and 60 min) and backwash duration (normally between 30 and 120 s) were entered as set-points in the control system. The process begins with the filtration sequence under constant flux dead-end mode until reaching a pre-determined filtration duration. Subsequently a backwash sequence ensues to hydraulically clean up the membrane within a pre-determined backwash duration. The next filtration sequence shall be repeated after the backwash sequence and these two sequences shall continue to operate alternately until a chemical cleaning of the membrane is required. This conventional set-points control system was implemented on-line using the UF experimental system to gather the required data for analysis.

2.2. ANN control system for UF process

Development of the ANN control system requires relevant training data from the UF experimental system. In order to train the ANN model and controllers, on-line TMP profiles and laboratory analysis data were compiled as the training data. Fluctuation of feed water characteristics have been known as one of the major challenges in water treatment processes (Ramírez et al., 2017). A series of filtration experiments with feed water samples of various turbidity measured in Nephelometric Turbidity Units (NTU) from the river were fed to the UF experimental system. A filtration sequence of 60 min was conducted for each feed water samples. River water samples with turbidity of between 5 NTU to 30 NTU were analysed for its turbidity and solids concentrations. Subsequently a graph correlating the river water turbidity and its solids concentrations was established. The ANN control system consisted of two major components which were the ANN predictive model (utilized to estimate α) and the ANN controllers (utilized to control the filtration and backwash durations)

2.2.1. ANN predictive model

In order to implement this advanced control system, an ANN predictive model was utilize to estimate the specific cake resistance or α in real-time. Relevant inputs were fed into the ANN predictive model to estimate α as shown in Fig. 4. According to literature report, α is strongly related to physical properties such as particle size distribution and shape of the feed water (Bourcier et al., 2016). Laborious experiments with advanced analysis equipment are generally required to determine values of α during filtration (Peiris et al., 2013; Chen et al., 2014). Using the ANN predictive model to estimate α in real-time significantly reduces the duration required for conventional laboratory analysis on this parameter. Inputs data of the feed water turbidity, on-line TMP, filtration time and the immediate past value of α (α_{t-1}) were fed into the predictive model to estimate the current value of α (α_t). This is known as dynamic ANN modelling whereby the immediate past value of the output is fed back as input into the model to allow a much more accurate prediction (Gautam and Soh, 2015). The estimated values of α by the ANN predictive model is then fed into the ANN controller No. 1 as input for the estimation of the filtration duration as shown in Fig. 6.

Another important physical parameter which required estimation was the feed water solids concentration or c_s. The correlation between feed water turbidity and c_s could be determined experimentally with simple laboratory analysis. Both α and c_s were reported as potential membrane fouling parameters in UF systems (Pontié et al., 2012). The main objective of estimating the values of α and c_s was to determine the potential membrane fouling propensity represented by the product of αc_s. In this research, the ANN predictive model provides a convenience tool to rapidly estimate values of α in real-time. Detailed procedures on the development of the ANN predictive model to estimate values of α has been reported in literature (Chew et al., 2017).

2.2.2. ANN controllers

The constant flux dead-end UF process operation consists of filtration and backwash sequences as shown in Fig. 5. These two sequences operate alternately until a chemical cleaning is required after 12 h of continuous operations. During filtration sequence, relevant inputs such as estimated values of α by the ANN predictive model and other relevant data were continuously fed into the ANN controller No. 1 (indicated in Fig. 6) to determine the filtration duration. When the filtration sequence ends, ANN controller No. 2 shall be initiated to determine the backwash duration based on the on-line data (TMP_{rev} and V_{bw}). The whole process control loop with the ANN control system is illustrated in a schematic diagram shown in Fig. 6.

The filtration sequence would continue until ANN controller No. 1 gives out an output signal to cease the sequence and subsequently initiate the backwash sequence. Backwash sequence commences when signal was received by ANN controller No. 2 (indicated in Fig. 6). ANN controller No. 2 shall decide the backwash duration based on the relevant inputs. Once the backwash sequence has been completed, all the designated control valves and pumps shall be switched over to initiate another filtration sequence. All the relevant inputs and outputs of the system have been further elaborated in the subsequent sections.

2.2.3. Differences between the ANN and conventional control systems

There are significant differences between the ANN and conventional control systems for the constant flux dead-end UF process. Conventional control system pre-determined the filtration and backwash durations. Once these set-points have been reached,

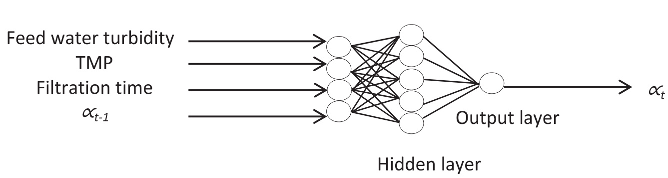


Fig. 4. Inputs and outputs of the ANN predictive model.

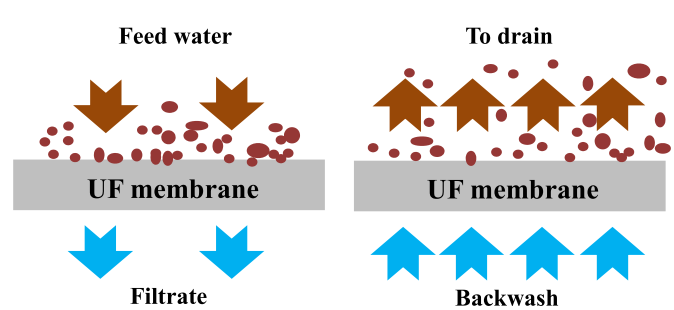


Fig. 5. Illustration of the filtration and backwash sequences.

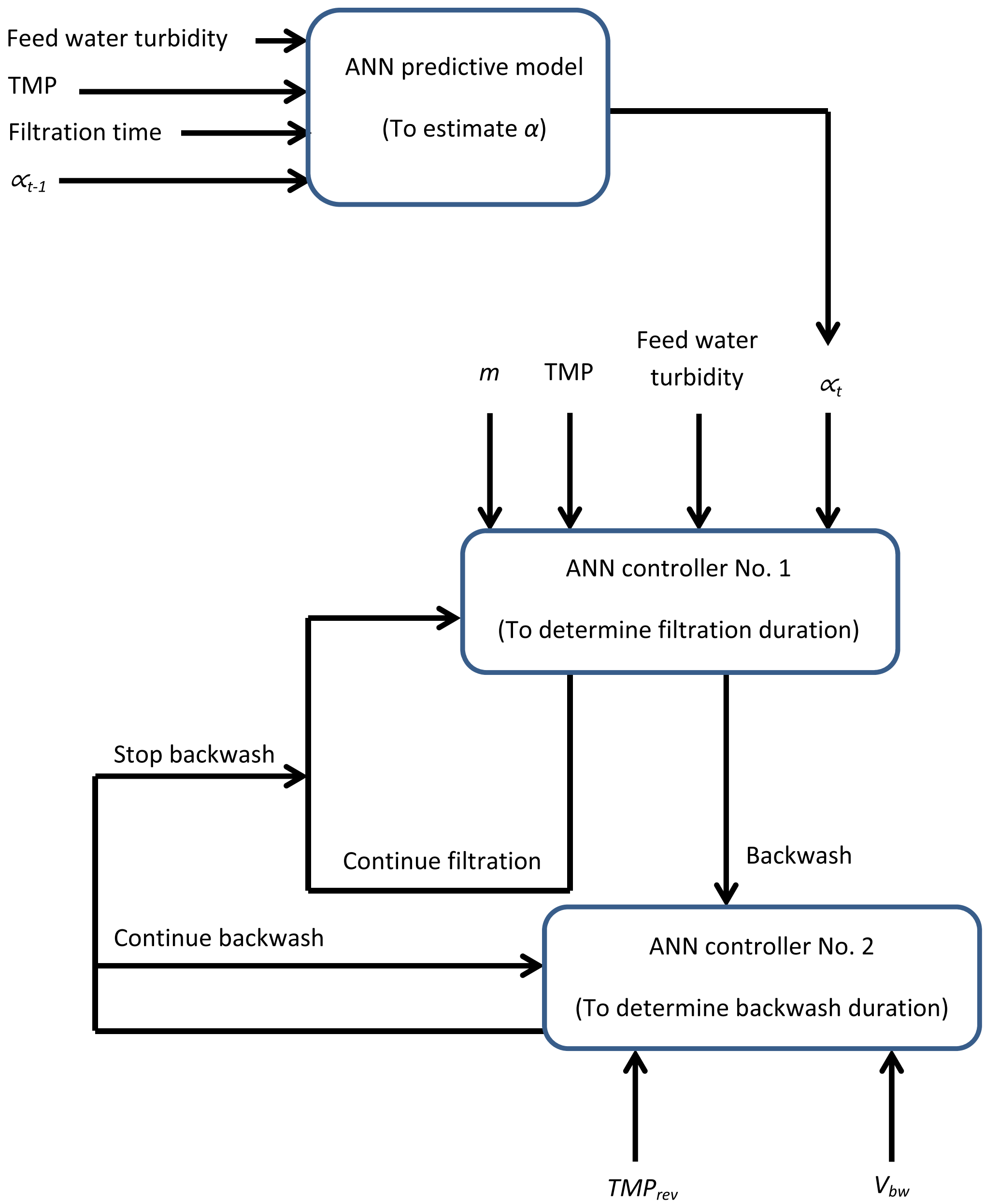


Fig. 6. Process control loop with ANN control system.

the controller would switch to the next sequence. Under the conventional set-points control system for the UF process, minimum two set-points are required; filtration duration and backwash duration set-points. A maximum allowable TMP set-point during filtration sequence is optional and acts as a precaution measure.

The ANN control system offers a distinctive advantage over the conventional set-points control system because the former takes into account the characteristic changes of the feed water. When the feed water characteristic changes (eg. turbidity), the ANN predictive model would swiftly estimates the values of α to reflect on the fluctuations. The information shall be fed as input to the ANN controller No. 1 with other relevant data to determine the filtration duration. During the backwash sequence, ANN controller No. 2 would make a decision on the backwash duration depending on the inputs data shown in Fig. 6. This enables the ANN control system to have much more flexibility on both the filtration and backwash durations under various feed water samples.

3. Results and discussion

In this research, on-line process control utilizing the UF experimental system was conducted using the conventional set-points and the ANN control systems. The conventional set-points control has been practiced widely at industrial-scale UF membrane water treatment plants whereby the filtration and backwash durations have been pre-determined. In order to gather data for the ANN model and controllers training, open-loop filtration data was obtained with the UF experimental system. Under the ANN control system there were 3 individually trained ANN (1 predictive model and 2 controllers) to replace the conventional set-points control system. Comparisons of the experimental results between the performance of both the conventional and ANN control systems were made. Actual operational information from an industrial-scale UF membrane water treatment plant was obtained in order to replicate the same condition on the UF experimental system.

Table 1
Operational parameters of the UF experimental system.

Parameters	UF experimental system
UF membrane type	Hollow fibre (modified PES)
Feed water source	River water
Total membrane surface area	1.0 m^2
Filtration flux	80 $L/m^2.hr$
Backwash flux	230 $L/m^2.hr$
Filtration duration	30 min
Backwash duration	60 s

Similar river water source and UF membrane utilized in the industrial-scale UF membrane water treatment plant was used in the UF experimental system.

3.1. Conventional set-points control system

Previous case studies of an industrial-scale UF membrane water treatment plant was taken as reference for the set-points of the conventional control system (Chew et al., 2015, 2016). This water treatment plant was operating under constant flux dead-end filtration mode and similar operational condition was implemented on the UF experimental system. The same river source to the water treatment plant was utilized as feed water to the UF experimental system. Similar hollow fibre UF membrane made from modified PES utilized in the water treatment plant was used in all the experiments. Table 1 shows the operational parameters of the UF experimental system.

The SCADA of the UF experimental system was programmed to record the on-line TMP data during operation. For every 30 min of filtration sequence, a 60 s backwash sequence ensues for the membrane cleaning. The feed water turbidity was analysed and recorded at the beginning of each filtration sequence. A recommended maximum limit of 20 NTU feed water turbidity have been imposed on the industrial-scale UF membrane water treatment plant to ensure optimum performance for the direct feed UF process. Under normal weather conditions the feed water turbidity was usually between 8 NTU to 15 NTU. Figs. 7 and 8 show the on-line TMP profiles recorded using the UF experimental system for feed water samples of 8 NTU and 18 NTU respectively.

All the TMP profiles shown in Figs. 7 and 8 have indicated similar pattern with gradual increase of TMP during the filtration sequences. Initially the TMP readings were between 0.36 and 0.38 Bar and increased to between 0.41 and 0.43 Bar after 30 min of filtration sequence. The TMP readings returned back to between 0.36 and 0.38 Bar after the 60 s backwash sequences. This indicates that the intermittent hydraulic backwash was capable of cleaning the membrane and restored back its permeability in the next filtration sequence.

3.2. Conventional set-points control system for water treatment and its limitations

The conventional set-points or feed-back control system is widely implemented on industrial-scale UF membrane water treatment plants for the convenience and simplicity of operations

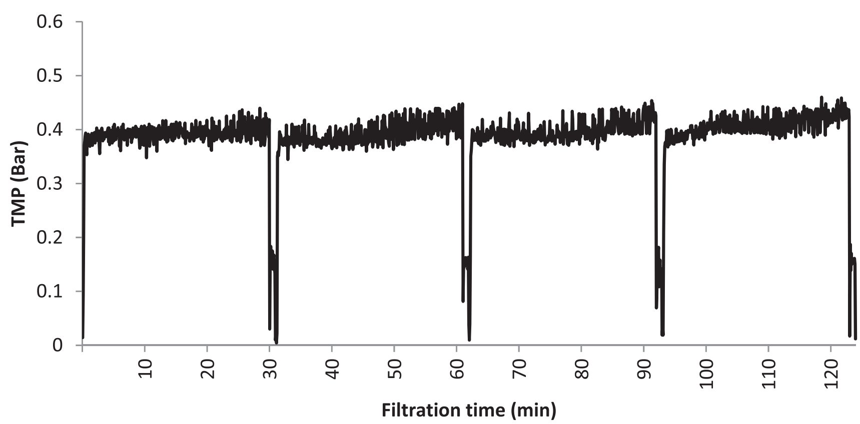


Fig. 7. On-line TMP profiles with feed water turbidity of 8 NTU.

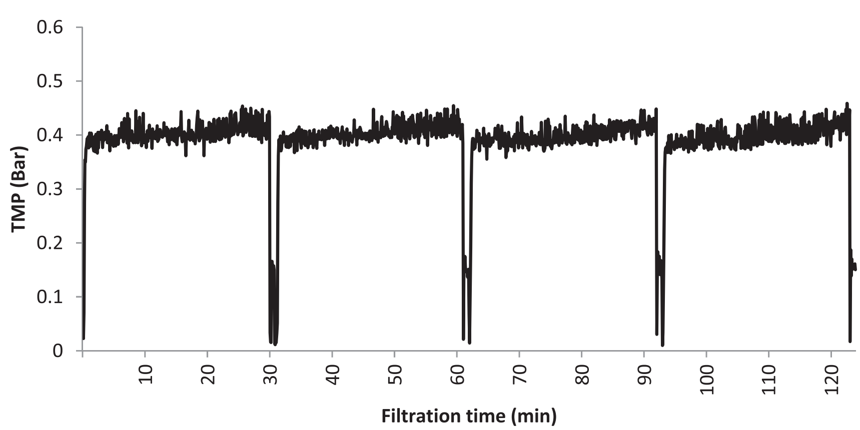


Fig. 8. On-line TMP profiles with feed water turbidity of 18 NTU.

(Cogan and Chellam, 2014). It only requires pre-determined values or set-points to be entered into the control system to initiate subsequent sequences (Alphonsus and Abdullah, 2016). Measured parameters such as TMP, filtration and backwash time are constantly feed-back to the control system for comparison with the set-points. Usually filtration duration and the maximum allowable TMP are entered as set-points for the filtration sequence while only backwash duration set-point is required for the backwash sequence. Under normal circumstances the filtration duration set-point would triggered the next backwash sequence and not the maximum allowable TMP set-point. The maximum allowable TMP set-point acts as a precaution measure in case there is any abnormal feed water composition with very high solids concentration enters the system. High solids loading entering the system could increase the TMP values significantly within a short period of time and possibly causing damages to the UF membrane modules. The maximum allowable TMP set-point is utilized to prevent excessive pressure on the UF membrane modules. Control set-points are normally provided by design engineers or plant managers which might not reflects the necessary changes to the actual process from time to time (Wang et al., 2016).

Control action in membrane systems such as backwash is unable to fully restore initial operating conditions due to irreversible membrane fouling (Rabuni et al., 2015). Over prolong continuous operation period of usually between 3 and 6 months, irreversible membrane fouling causes the initial TMP of the filtration sequence to increase gradually even after backwash. If a TMP set-point is utilized for process control, the duration of each filtration sequence would be reduced when the set-point is reached. Under such condition the productivity decreases due to shorter filtration duration and more frequent backwash sequences (Smith et al., 2006). This is one of the reasons filtration duration set-point is more preferable than a TMP set-point for industrial-scale UF membrane water treatment plant. The production volume would remain the same although higher feed water pressure is required to overcome the increase of TMP due to irreversible membrane fouling.

Similarly a backwash duration set-point is more preferable than a pressure set-point in membrane systems. Irreversible membrane fouling also causes higher back pressure or reverse TMP (TMP_{rev}) during backwash which could not be reduced even after prolong hydraulic cleaning. Under constant flux backwash sequence, the total volume of water utilized for hydraulic cleaning and the TMP_{rev} are important parameters to evaluate the cleaning efficiency. Advanced control such as ANN is capable of "learning" and adapts to current conditions of membrane fouling in the system to decide on the duration of backwash sequences.

For low pressure UF processes in drinking water applications, the correlation between specific flux and TMP is mathematically non-linear. The significance of this non-linear correlation is that it complicates the interpretation of membrane fouling (Boyd and Duranceau, 2013). Irreversible membrane fouling causes decrease in specific flux and gradual increase in TMP. Using pressure (TMP and reverse TMP) as set-points in the conventional control system to trigger the filtration and backwash sequences are not practical as the set-points would need to be increased periodically and incurred inconsistent filtrate production. Unlike the pressure set-points, using durations (filtration and backwash) as set-points ensure consistent filtrate production. The drawback of using pre-determined set-points (both pressure and duration) is the lacks of capability to predict potential membrane fouling propensity (αc_s) for various feed water characteristics. Under conventional set-points control system, the amount of water losses is the same irrespective of the feed water turbidity due to the pre-determined filtration and backwash duration set-points. Advanced control system such as ANN has the advantage of estimating the potential membrane fouling propensity data and prolongs the filtration sequence for low turbidity feed water. The ANN control system could also be trained to ensure a thorough backwash based on the on-line TMP_{rev} data to minimize membrane fouling. This is a novel control method which ensures acceptable potential membrane fouling propensity and reduction of water losses for the UF dead-end constant flux process.

3.3. Data collection for ANN training

River water samples of different turbidity were analysed for its solids concentrations. In order to establish correlation between the solids concentrations and the turbidity of the feed water, the data were plotted on a graph shown in Fig. 9. The analyses of the water samples solids concentrations were conducted in accordance to American Public Health Association (APHA) guidelines which require between 10 and 15 h for the results. Fig. 9 indicated a linear correlation could be established between the feed water solids concentrations and turbidity data for samples between 5 NTU to 30

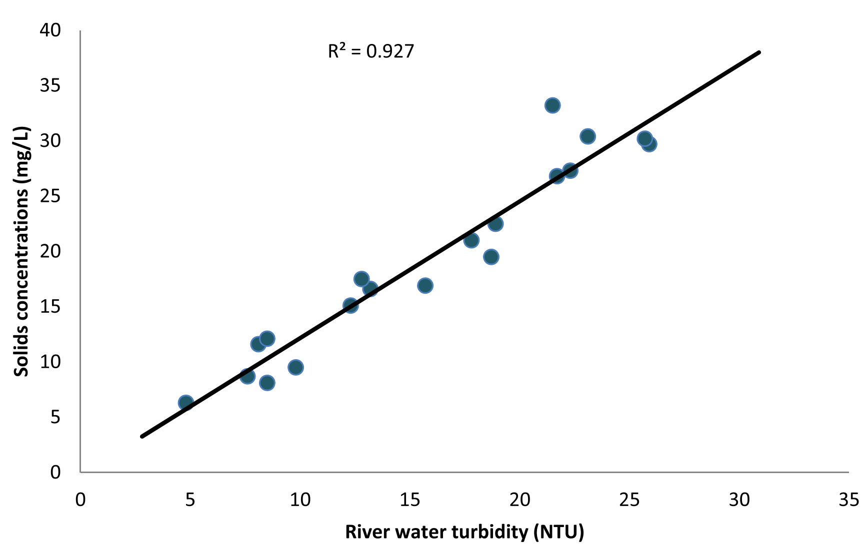


Fig. 9. Correlation between river water solids concentrations and turbidity.

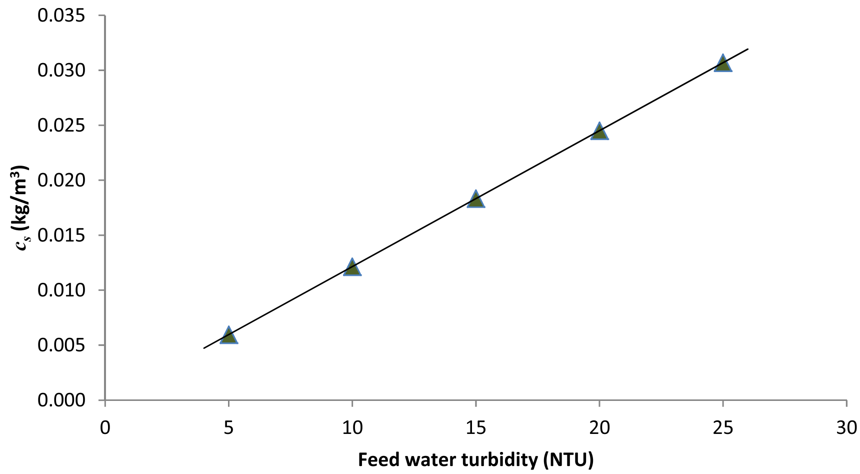


Fig. 10. Estimated values of c_s for various feed water samples of different turbidity.

NTU. The industrial-scale UF membrane water treatment plant mentioned earlier was designed for direct feed with feed water turbidity of 20 NTU or below. Experiments with similar feed water turbidity range were conducted using the UF experimental system.

It was reported in literature that the product of specific cake resistance (α) and the feed water solids concentration (c_s) is an indication of the potential membrane fouling propensity (Boerlage et al., 2004). There are possibilities to extend filtration duration of the constant flux dead-end UF process to a common αc_s value and reduce water losses with lower frequency of backwash sequences. In order to gather the required filtration data, feed water samples with different turbidity from the river were collected. These various turbidity feed water samples were obtained by collecting 1 m^3 of the river water with turbidity of between 30 NTU to 40 NTU in a tank. Subsequently the river water in the tank was allowed to settle between 1 and 12 h. The top layer of the water was scoop out from the tank to produce various turbidity feed water samples (5 NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU). These water samples were fed into the UF experimental system for 60 min each filtration sequence under constant flux dead-end mode to obtain the TMP profiles.

Darcy's equation in Eqn. (1) was utilized to investigate the changes of α for each feed water samples. In Eqn. (1), J represents the filtrate flux, ΔP the TMP, μ the filtrate viscosity, R_m the membrane resistance, α the specific cake resistance and m is the cake mass per unit membrane area. The membrane resistance (R_m) was determined through normal procedures reported in literature (Roy and De, 2015). It was reported that both α and m are parameters which were known to be difficult to determine experimentally (Boerlage et al., 2004). In this research study, efforts were made to estimate these 2 parameters with simple laboratory analysis method and by using the ANN predictive model. The parameter c_s could be estimated based on the correlation of feed water solids concentrations and turbidity shown in Fig. 9. By applying Eqn. (2), the parameter m could be easily estimated for the constant flux dead-end UF process. In Eqn. (2), c_s is the feed water solids concentration, V_s is the volume of the feed water and A is the membrane surface area. Since all the experiments in this study were conducted under constant flux dead-end filtration mode, both V_s and A were known values.

$$J = \frac{\Delta P}{\mu(R_m + \alpha m)} \tag{1}$$

$$m = \frac{c_s V_s}{A} \tag{2}$$

Estimation of c_s of the feed water samples (5NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU) were conducted by utilizing the solids concentrations and turbidity correlation in Fig. 9. Fig. 10 shows the estimated c_s values based on the respective turbidity of the feed water samples. Fig. 11 shows the increase of m for various feed water samples of different turbidity during filtration estimated from Eqn. (2).

Gradual increase of m for the samples were expected since all the experiments were conducted under constant flux dead-end filtration conditions with feed water remains the same turbidity throughout the whole 60 min. Higher turbidity feed water samples represent higher loading of solids/cake mass or m values against filtration time. Estimation of the specific cake resistance (α) could be conducted using Eqn. (1) once the value of m for each samples have been determined. In this equation, all the other parameters such as J, μ and R_m were constant values while ΔP were obtained from the TMP profiles using the various feed water samples (5 NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU). This permits a straight forward estimation on the values of α using Eqn. (1). Fig. 12 shows the estimated values of α against the filtration time for various feed water samples.

Fig. 12 shows that α approach constant values for all the feed water samples after 20 min of filtration time. There was also an interesting observation whereby the ultimate values of α increase as the feed water turbidity of the samples decrease. Similar observation has been reported in literature stating that the values of α increase with decreasing solids concentrations of the feed solution samples in membrane filtration experiments (Chang and Kim, 2005). It was suggested that for low solids concentrations of the feed solution samples, α decreases with increasing solids concentrations. Literature has reported that the value of αc_s represents an indicative of potential membrane fouling propensity (Boerlage et al. 1998, 2000, 2003, 2004).

The industrial-scale UF membrane water treatment plant mentioned earlier implements a cycle of 30 min filtration duration followed by 60 s of backwash duration for feed water turbidity of not exceeding 20 NTU. Most of the time the river water turbidity was below 20 NTU except during heavy rainfalls whereby the turbidity could shoots up to more than 50 NTU. The 30 min filtration duration with feed water turbidity of 20 NTU was assumed as the basis of the recommended potential membrane fouling

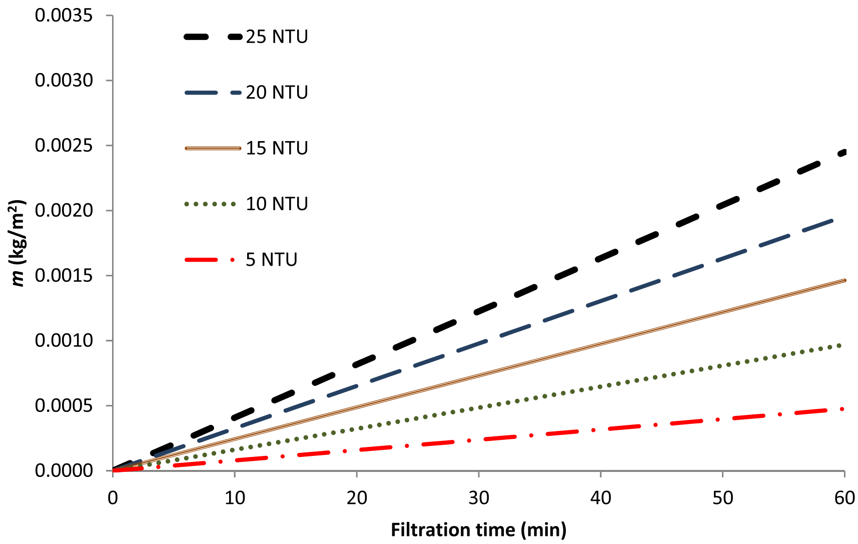


Fig. 11. Increase of cake mass per unit membrane area (m) during filtration.

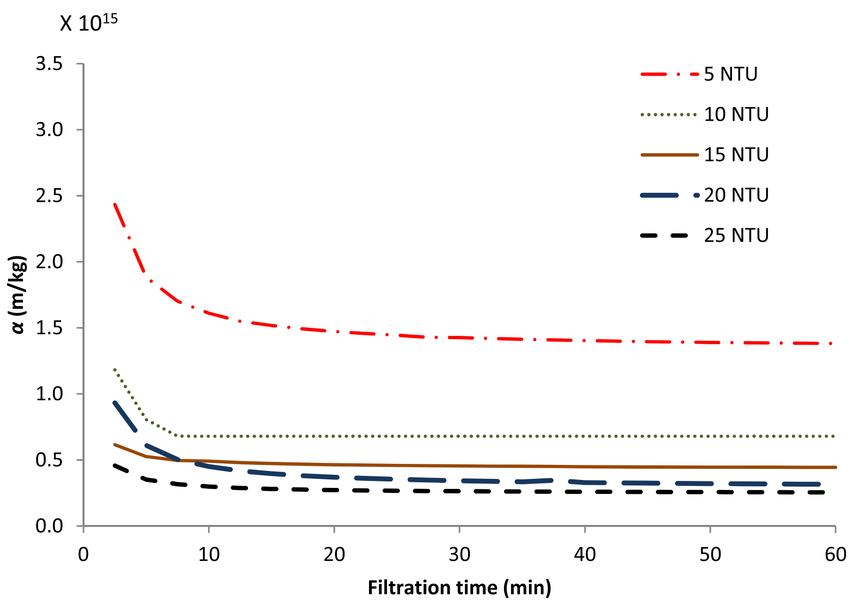


Fig. 12. Estimated specific cake resistance (α) during filtration.

Table 2
Estimated values of α and c_s for various feed water samples.

	5 NTU	10 NTU	15 NTU	20 NTU	25 NTU
α (m/kg)	13.85×10^{14}	6.79×10^{14}	4.48×10^{14}	**3.42×10^{14}**	2.67×10^{14}
c_s (kg/m^3)	0.00596	0.01215	0.01833	**0.02451**	0.03070
αc_s (m^{-2})	8.25×10^{12}	8.24×10^{12}	8.21×10^{12}	**8.38×10^{12}**	8.20×10^{12}
Filtration duration	55 min	50 min	40 min	**30 min**	25 min

propensity for this UF process. Table 2 shows the estimated values of α and c_s from Figs. 10 and 12 for the feed water samples.

Data shown in Table 2 have indicated that based on the recommended 30 min filtration duration with feed water turbidity of 20 NTU, the αc_s was 8.38×10^{12} m^{-2}. As mentioned earlier, the value of αc_s was suggested to represent the potential membrane fouling propensity and it should be kept below the recommended value to mitigate membrane fouling issues. Analysis of all the feed water samples shown in Table 2 have indicated that in order to achieve αc_s less than 8.38×10^{12} m^{-2}, the samples below 20 NTU (5 NTU, 10 NTU and 15 NTU) could proceed for more than 30 min filtration duration while the 25 NTU sample could only undergo filtration for 25 min before reaching near to the recommended αc_s value of 8.38×10^{12} m^{-2}.

The river water turbidity was directly proportional to c_s as shown in Fig. 9. Feed water with low turbidity represents less solids

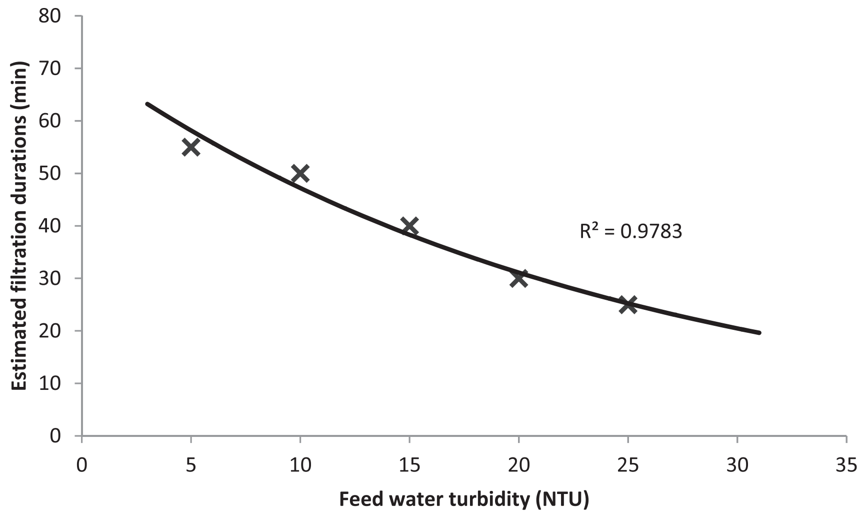


Fig. 13. Estimated filtration durations against feed water turbidity.

loading on the UF membrane which permits longer filtration duration. Under the constant flux dead-end filtration mode, αc_s represents the cake resistance which is an indication for potential membrane fouling propensity. The potential membrane fouling propensity increases in accordance to the cake resistance. Using the αc_s values as indication for different feed water samples could provide an alternative control method to ensure acceptable potential membrane fouling propensity while increases filtration durations for low turbidity feed water samples. Fig. 13 shows the estimated filtration duration based on Table 2 which utilized the analysis of the αc_s values for each feed water samples. As the turbidity of the feed water samples increase, the estimated filtration durations decrease as indicated in Fig. 13.

3.4. ANN predictive model and controllers

Based on all the data collected through the UF experimental system and laboratory analysis, three ANN model/controllers were trained. These include the ANN predictive model, ANN controller No. 1 and ANN controller No. 2 as shown in Fig. 6. The ANN predictive model was developed and further elaborated in a previous research work (Chew et al., 2017). This ANN predictive model was developed as part of a hybrid model for the estimation of α. The ANN controller No. 1 was trained to control the filtration duration before a backwash sequence was required. Data obtained from Figs. 9–13 was utilized to train this controller. The ANN controller No. 1 provides outputs of either 1 (continue filtration) or 0 (stop filtration) according to the relevant inputs. Once the filtration sequence ends, a backwash sequence shall be initiated.

The ANN controller No. 2 was trained to ensure an efficient backwash sequence by observing the reverse TMP (TMP_{rev}) and the total volume of water utilized during backwash (V_{bw}). This controller provides outputs of either 1 (continue backwash) or 0 (stop backwash) based on these inputs. Once the backwash sequence ends, the next filtration sequence commences. The whole cycle of filtration and backwash sequences would then be repeated again. Table 3 shows the inputs and outputs of all the ANN model and controllers.

All three ANN model/controllers were individually trained with the relevant data. Subsequently all these model and controllers were incorporated into the SCADA software for on-line implementation with the UF experimental system. Experiments were conducted using this ANN control system with feed water samples from the river source. These experiments were conducted under the same constant flux dead-end filtration mode with filtration and backwash flux rates shown in Table 1.

Fig. 14 shows the on-line TMP profiles and outputs from the ANN model/controllers for feed water sample with 8 NTU of turbidity. The results in Fig. 14(a) have indicated that the TMP increases gradually from 0.37 Bar to 0.46 Bar during the filtration sequence of 50 min. After a backwash sequence, the TMP dropped back to its initial value of 0.37 Bar in the next filtration sequence. Fig. 14(b) shows the estimated values of α by the ANN predictive model during the filtration sequences. The estimated values of α remains almost the same at 8.52×10^{14} m/kg throughout the filtration sequences. Fig. 14(c) and (d) indicated the outputs from ANN controller No. 1 and ANN controller No. 2 respectively. During filtration sequence, ANN controller No. 1 allowed 50 min filtration duration based on the inputs data provided. Once the filtration sequence stops, ANN controller No. 2 was initiated to commence the backwash sequence. This controller decides the duration of the backwash sequence based on the relevant inputs data. The controller allowed 51 s of backwash duration. Once the backwash sequence has stopped, the next filtration sequence commences and

Table 3
Inputs and outputs of the ANN model and controllers.

	ANN predictive model	ANN controller No. 1 (filtration sequence)	ANN controller No. 2 (backwash sequence)
Inputs	* Feed water turbidity * On-line TMP * Filtration time * Past values of α (α_{t-1})	* Feed water turbidity * On-line TMP * Current values of α (α_t) * m	* On-line reverse TMP (TMP_{rev}) * Volume of backwash water used (V_{bw})
Outputs	* Current values of α (α_t)	* 1 (continue filtration) * 0 (stop filtration)	* 1 (continue backwash) * 0 (stop backwash)

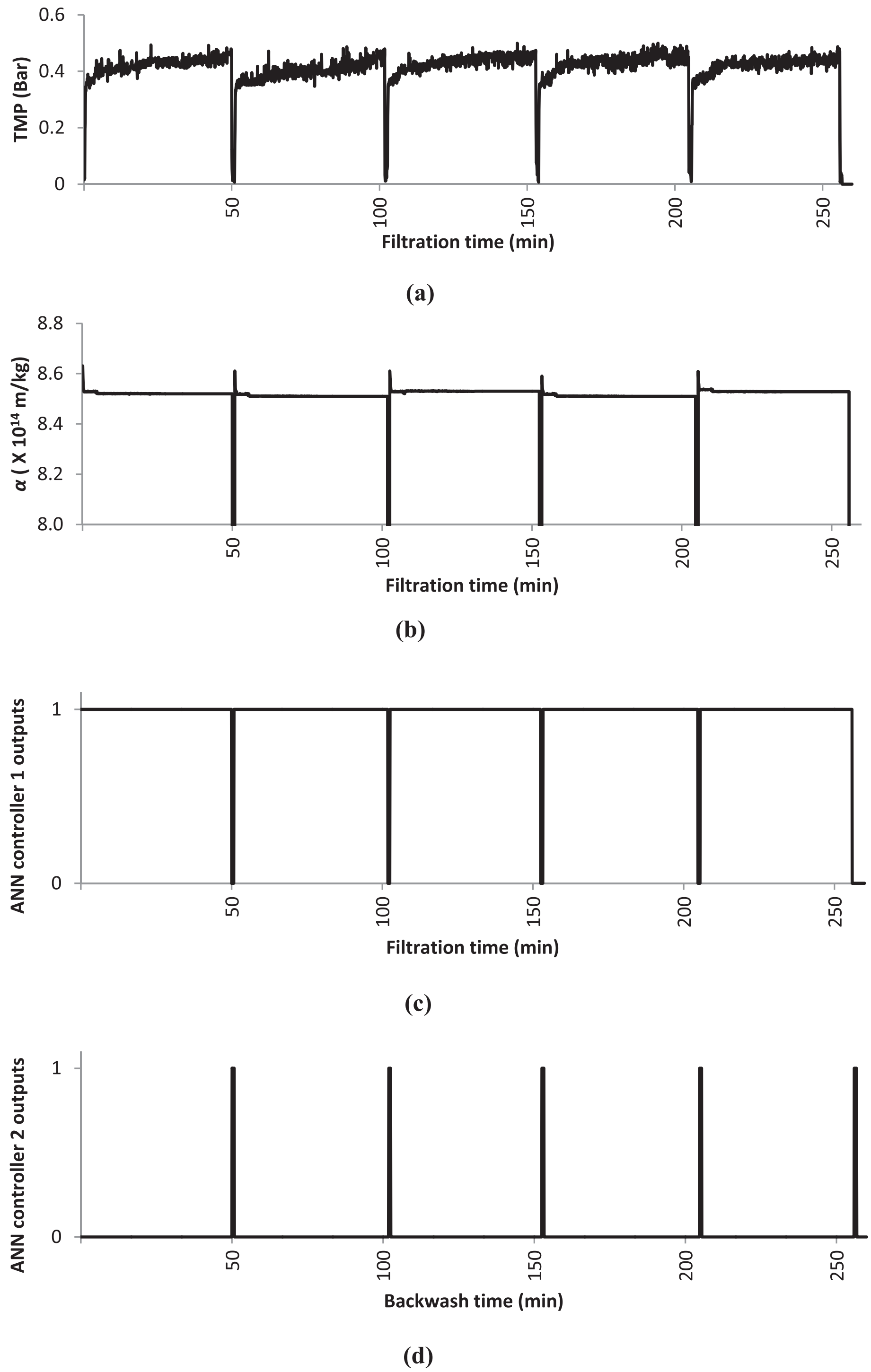


Fig. 14. (a) TMP profiles during filtration (8 NTU sample), (b) Outputs from ANN predictive model (8 NTU sample), (c) Outputs from ANN controller No.1 (8 NTU sample), (d) Outputs from ANN controller No.2 (8 NTU sample).

the cycle was repeated again. This filtration-backwash cycle was repeated five times to determine the consistency of the ANN control system on the same feed water sample with 8 NTU of turbidity. Table 4 summarizes the data from the five filtration-backwash cycles in Fig. 14. The value of c_s for this 8 NTU feed water sample was estimated to be 9.67×10^{-3} kg/m^3 from Fig. 10 and the average value of αc_s for the five filtration sequences was 8.24×10^{12} m^{-2}.

The ANN control system was also implemented on higher turbidity feed water sample of 18 NTU with the same procedures. Results of the TMP profiles and the ANN control system outputs for the 18 NTU feed water sample were depicted in Fig. 15. During the filtration sequence even though the initial TMP of 0.37 Bar observed was similar to the sample of 8 NTU, the final TMP was much lower at only 0.42 Bar as shown in Fig. 15(a). The ANN predictive model has estimated the values of α as 3.64×10^{14} m/kg indicated in Fig. 15(b). Data shown in Fig. 15(c) indicated that the ANN controller No. 1 has limited the filtration duration to only 31 min due to the

Table 4
Summarized data from Fig. 14 (8 NTU sample).

	Initial TMP	Final TMP	α	Filtration duration	Backwash duration
1st sequence	0.37 Bar	0.46 Bar	8.52×10^{14} m/kg	50 min	50 s
2nd sequence	0.36 Bar	0.46 Bar	8.51×10^{14} m/kg	51 min	51 s
3rd sequence	0.38 Bar	0.45 Bar	8.53×10^{14} m/kg	50 min	51 s
4th sequence	0.38 Bar	0.46 Bar	8.51×10^{14} m/kg	51 min	50 s
5th sequence	0.37 Bar	0.46 Bar	8.53×10^{14} m/kg	50 min	51 s
Average	**0.37 Bar**	**0.46 Bar**	**8.52×10^{14} m/kg**	**50 min**	**51 s**

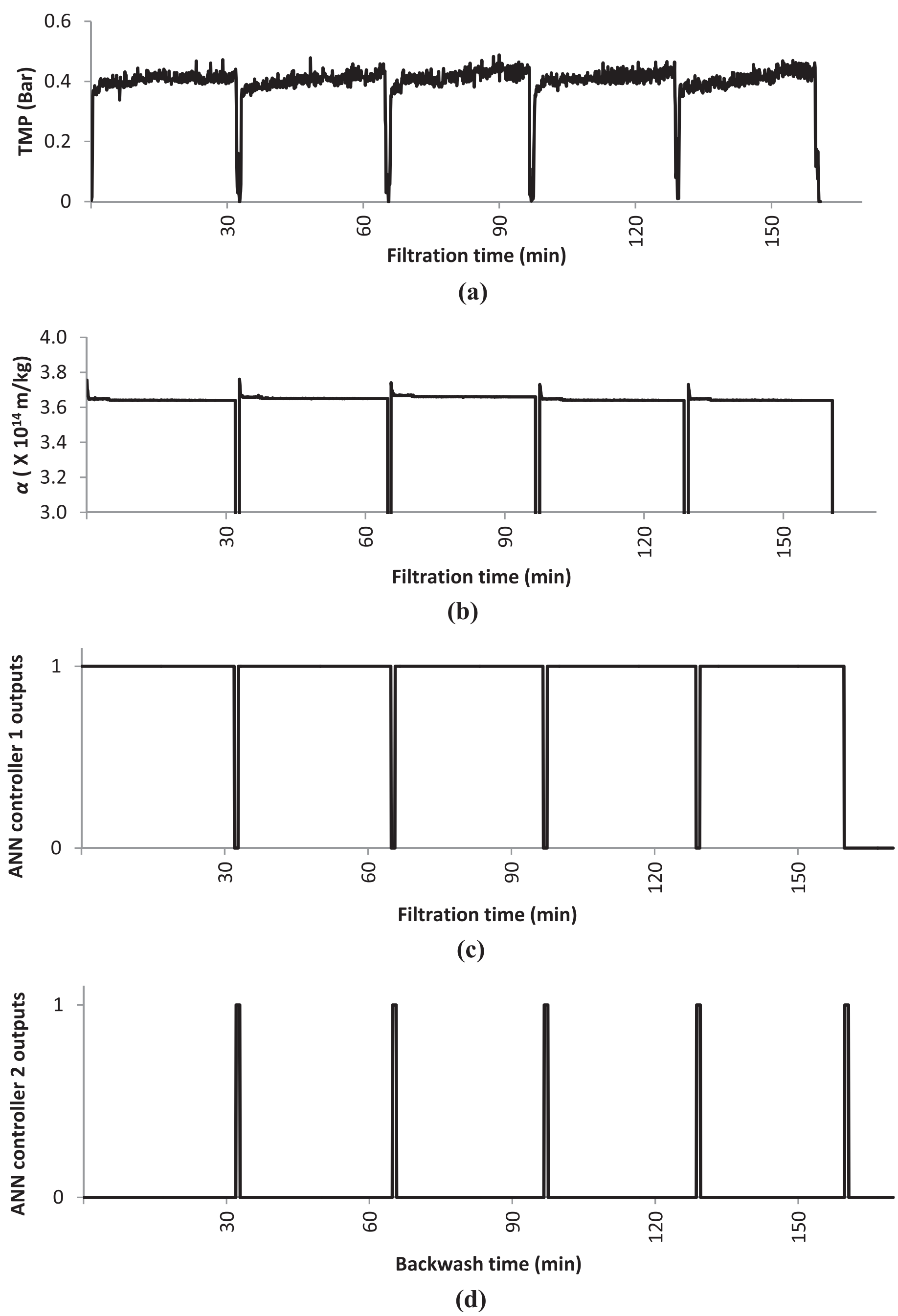


Fig. 15. (a) TMP profiles during filtration (18 NTU sample), (b) Outputs from ANN predictive model (18 NTU sample), (c) Outputs from ANN controller No.1 (18 NTU sample), (d) Outputs from ANN controller No.2 (18 NTU sample).

higher turbidity of the feed water. Once the filtration sequence stops, ANN controller No. 2 takes control of the backwash sequence. The backwash sequence stops after 51 s as shown in Fig. 15(d). Similar filtration-backwash cycle was repeated five times with the same 18 NTU feed water sample. Table 5 summarizes the data on Fig. 15. The estimated value of c_s for the 18 NTU feed water from

Table 5
Summarized data from Fig. 15 (18 NTU samples).

	Initial TMP	Final TMP	α	Filtration duration	Backwash duration
1st sequence	0.37 Bar	0.41 Bar	3.64×10^{14} m/kg	32 min	50 s
2nd sequence	0.37 Bar	0.42 Bar	3.65×10^{14} m/kg	32 min	51 s
3rd sequence	0.38 Bar	0.43 Bar	3.66×10^{14} m/kg	31 min	51 s
4th sequence	0.37 Bar	0.42 Bar	3.64×10^{14} m/kg	31 min	50 s
5th sequence	0.37 Bar	0.42 Bar	3.64×10^{14} m/kg	31 min	51 s
Average	**0.37 Bar**	**0.42 Bar**	**3.64×10^{14} m/kg**	**31 min**	**51 s**

Fig. 10 was 22.04×10^{-3} kg/m^3. Average value of αc_s for this sample was 8.03×10^{12} m^{-2}.

All the ANN model/controllers were trained with data from feed water samples of various turbidity ranging from 5 NTU to 25 NTU. The average river water turbidity was between 8 NTU to 15 NTU. It was considered abnormal conditions for the river water turbidity to exceed 20 NTU. These abnormal conditions were usually caused by surface run-off due to heavy rainfalls. Most direct feed UF membrane water treatment systems for surface water were designed to handle moderate and low turbidity feed water to reduce potential membrane fouling propensity.

Even though this ANN control system was designed to cater for feed water with turbidity of 20 NTU and below, efforts were made to test this control system with much higher turbidity of feed water from the same river source. Table 6 shows the results obtained from experiments with feed water sample of 30 NTU which was also beyond the training data of the ANN model and controllers.

Comparing data from Table 6 and Fig. 13 indicated that the filtration duration of 24 min for the 30 NTU feed water sample under the ANN control system was much longer than expected. The estimated filtration duration for a 30 NTU feed water sample was only 20 min. Such discrepancies occurred mainly because of the training data range for all the ANN model and controllers. As mentioned earlier, the ANN control system was designed for feed water of 20 NTU and below. The training data was obtained from feed water samples with turbidity ranging from 5 NTU to 25 NTU. Even though the higher turbidity feed water of 30 NTU was not covered in the training data, the ANN controller No. 1 was able to reduce the filtration duration to 24 min. It is necessary to ensure that the working range of the ANN control system is within the training data range to obtain satisfactory results.

There were also possibilities that the feed water solids concentrations and turbidity correlation established in Fig. 9 might have abruptly changed due to various conditions of the river water. The feed water characteristics changes would cause the potential membrane fouling propensity to increase and rendered the estimation of α and c_s inaccurate. This might results in higher accumulation of solids on the membrane surface before a backwash sequence was initiated. The ANN controller No. 2 was trained with data of reverse TMP (TMP_{rev}) to ensure thorough cleaning of the membrane during backwash sequences. Reverse TMP (TMP_{rev}) is the difference of hydraulic pressure between the filtrate port (clean water inlet) and the feed port (discharge to drain) from the UF membrane module during backwash sequence. The higher value of TMP_{rev} indicates higher resistance caused by accumulated solids on the membrane surface during backwash sequence.

Table 6
Summarized data from feed water sample with 30 NTU.

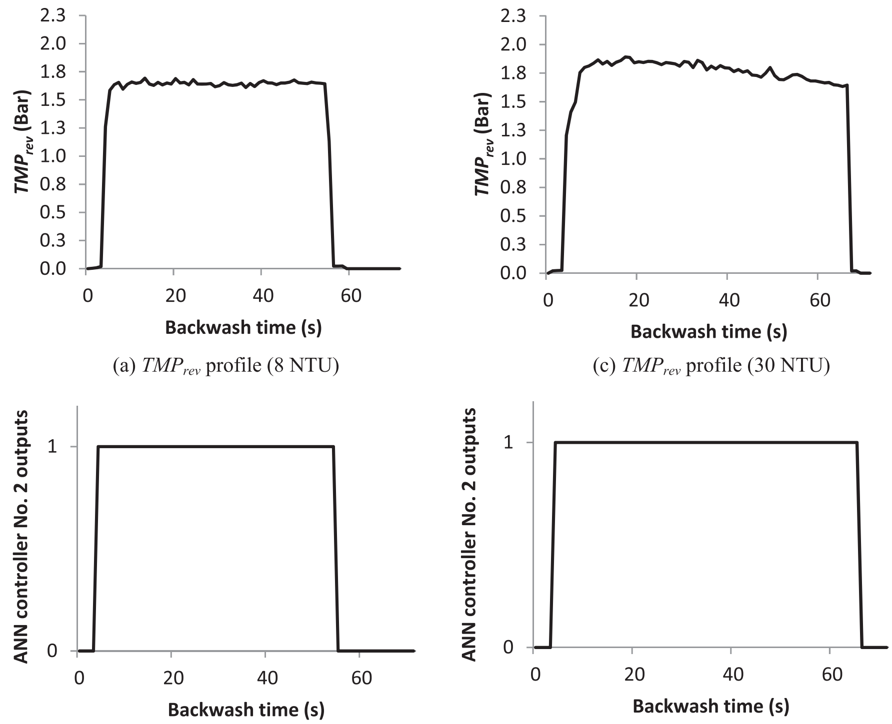
	Initial TMP	Final TMP	Filtration duration	Backwash duration
1st cycle	0.36 Bar	0.41 Bar	24 min	50 s
2nd cycle	0.37 Bar	0.42 Bar	24 min	51 s
3rd cycle	0.37 Bar	0.42 Bar	25 min	51 s
4th cycle	0.37 Bar	0.40 Bar	25 min	50 s
5th cycle	0.36 Bar	0.41 Bar	24 min	50 s
Average	**0.37 Bar**	**0.41 Bar**	**24 min**	**51 s**

Under normal filtration sequence operation conditions, the product of αc_s should be approximately 8.38×10^{12} m^{-2} before the filtration sequence stops and backwash sequence is initiated. River water characteristic changes might cause significantly higher value of αc_s than the estimated value from the ANN control system. In order to simulate a higher value of αc_s, a 30 NTU feed water sample from the same river was fed to the UF experimental system but the turbidity was entered as 8 NTU into the SCADA system. The ANN control system considered this feed water sample turbidity as 8 NTU based on the turbidity data entered into the system. Results in Table 4 indicated that the filtration duration would be 50 min followed by a 51 s of backwash duration under normal condition for a feed water sample with 8 NTU of turbidity. Higher value of αc_s or potential membrane fouling propensity (more than 8.38×10^{12} m^{-2}) was generated in this experiment at the end of the filtration sequence.

Fig. 16 shows the TMP_{rev} profiles and the ANN controller No. 2 outputs for both the 8 NTU and 30 NTU feed water samples. ANN controller No.1 limits the filtration duration of the 8 NTU feed water sample to 50 min before initiating a 51 s of backwash sequence. The TMP_{rev} profile for the 8 NTU feed water sample is shown in Fig. 16(a). During initial stage of the backwash sequence, the TMP_{rev} was 1.7 Bar and decreased to 1.6 Bar at the end of the 51 s backwash duration controlled by the ANN controller No. 2 indicated in Fig. 16(b). The backwash sequence removed accumulated solids from the membrane surface to reduce the resistance and caused the TMP_{rev} to decrease from 1.7 Bar to 1.6 Bar at the end of the sequence. Since the 30 NTU feed water sample was entered as 8 NTU turbidity in the system, the ANN controller No. 1 regulated the filtration duration to 50 min before initiating a backwash sequence. During the initial backwash sequence, the TMP_{rev} of the 30 NTU feed water sample clearly exhibited a much higher resistance of 1.9 Bar as shown in Fig. 16(c). Due to the higher accumulation of solids on the membrane for this feed water sample at the end of the filtration sequence, a much higher resistance was expected during the initial backwash sequence. Total backwash duration for the 30 NTU feed water sample was 62 s as shown in Fig. 16(d). This has indicated that the ANN controller No. 2 was able to allow longer backwash duration based on the TMP_{rev} and V_{bw} data to ensure much longer cleaning for the 30 NTU sample. Average backwash durations of 60 s or longer serve as an indication that the feed water characteristic might have changed and require further attention or maybe re-training of all the ANN model and controllers are necessary.

3.5. Comparisons between conventional set-points and ANN control systems

All the experimental results from the conventional set-points and ANN control systems were summarized in Table 7. The results obtained from the two feed water samples with different turbidity (8 NTU and 18 NTU) have been compared in various



(a) TMP_{rev} profile (8 NTU)
(c) TMP_{rev} profile (30 NTU)
(b) Outputs of ANN controller No. 2 (8 NTU)
(d) Outputs of ANN controller No. 2 (30 NTU)

Fig. 16. (a) TMP_{rev} profile (8 NTU), (b) Outputs of ANN controller No. 2 (8 NTU), (c) TMP_{rev} profile (30 NTU), (d) Outputs of ANN controller No. 2 (30 NTU), TMP_{rev} profiles and ANN controller No. 2 outputs.

Table 7
Results comparisons between conventional and ANN controllers.

Parameters	Conventional Control	ANN Control
Filtration duration		
8 NTU (Feed water)	30 min	50 min
18 NTU (Feed water)	30 min	31 min
Fouling propensity(αc_s)		
8 NTU (Feed water)	$8.38 \times 10^{12}\,m^{-2}$	$8.24 \times 10^{12}\,m^{-2}$
18 NTU (Feed water)	(based on 20 NTU only)	$8.03 \times 10^{12}\,m^{-2}$
Water losses (backwash)		
8 NTU (Feed water)	9.6%	4.9%
18 NTU (Feed water)	9.6%	7.9%
Initial TMP after backwash		
8 NTU (Feed water)	0.36–0.38 Bar	0.36–0.38 Bar
18 NTU (Feed water)	0.36–0.38 Bar	0.37–0.38 Bar

aspects such as filtration duration, potential membrane fouling propensity (αc_s), water losses due to backwashes and the initial filtration TMP after backwash sequences.

Conventional set-points control system utilized the pre-determined 30 min filtration duration as limit for all feed water samples with turbidity of 20 NTU and below. In Table 7 it was shown that irrespective of the feed water turbidity (both 8 NTU and 18 NTU samples), the filtration duration was fixed at 30 min before a backwash sequence was initiated. Under the conventional set-points control system the water losses due to backwash was fixed at 9.6%. After the backwash sequence the next filtration sequence commences with initial TMP of between 0.36 and 0.38 Bar which indicated a clean membrane surface has been restored. Comparison analysis shown in Table 7 highlighted the ANN control system capability to regulate the filtration durations based on the feed water samples turbidity and potential membrane fouling propensity. The potential membrane fouling propensity represented by αc_s for both the 8 NTU and 18 NTU samples were between $8.00 \times 10^{12}\,m^{-2}$ to $8.30 \times 10^{12}\,m^{-2}$ which were quite close to the reference value of $8.38 \times 10^{12}\,m^{-2}$. A few advantages could be noticed by using the ANN control system to replace the conventional set-points control system.

Firstly the ANN predictive model could estimate the values of α which varies with the feed water turbidity. This enables the system to estimate the potential membrane fouling propensity or αc_s of each feed water samples. The estimated values of αc_s should be approximately the recommended value of $8.38 \times 10^{12}\,m^{-2}$ to ensure an acceptable level of potential membrane fouling propensity is reached before a backwash sequence is initiated. This control system allowed feed water with low turbidity to undergo longer filtration duration and feed water with higher turbidity with shorter filtration duration while ensuring all of these feed water samples have similar potential membrane fouling propensity at the end of the filtration sequence.

The backwash sequence was triggered once the filtration sequence was completed and ANN controller No. 2 would determine the duration of the backwash sequence. Under normal circumstances, the backwash duration was between 50 and 51 s. There were situations whereby the overall water losses due to backwashes were significantly reduced to only 4.9% (8 NTU sample) by having longer filtration duration. The water losses for the conventional set-points control were 9.6% for both the feed water samples of 8 NTU and 18 NTU. In order to determine the efficiency of the backwash using the ANN control system, the initial TMP of the next filtration sequence after a backwash sequence was compared with the conventional control system. Both the conventional set-points and ANN control systems indicated similar initial TMP values of between 0.36 and 0.38 Bar after a backwash sequence which shows almost similar cleaning efficiency were achieved. The major drawback of the ANN control system is the requirement to re-train all the model and controllers if there were significant changes of the feed water characteristics.

3.6. Implications of reducing water losses for industrial-scale water treatment plants

Industrial-scale water treatment plants encounter numerous economic and environmental challenges in most regions of the world (Amini et al., 2015). Appropriate technology applied in these water treatment plants are required to ensure efficient operation to meet the stipulated quality and quantity of the treated water at the lowest possible overall environmental and economic costs (Abdulbaki et al., 2017). Electricity cost is one of the main operational expenditure for industrial-scale UF membrane water treatment plants. It has been reported that the specific electricity requirement for industrial-scale UF membrane water treatment plants was expected to be about 0.20 kWh/m^3 (Pearce, 2008). Specific electricity requirement could be significantly lowered down by reducing water losses (Lam et al., 2017). Higher recovery rate or lower water losses represent better efficiency in resources management and cost savings. Based on reported electricity tariff (denoted in United States Dollar or USD) of 0.0995 USD/kWh (Sharma et al., 2015), an industrial-scale UF membrane water treatment plant with treatment capacity of 5, 000 m^3/hr would require to pay electricity cost of 71, 640 USD/month. A mere 4.7% water losses reduction or electricity cost savings would translate to 3, 367 USD/month.

Global carbon emission from the fossil fuels electricity generation sector continues to grow in recent years (Wolfram et al., 2016). Reducing water losses not only cut-down the electricity cost, it also reduces carbon emission in the overall water treatment process. Regulating carbon emission is particularly important for countries that impose carbon tax or carbon trading (Qi and Chang, 2013). Efficient resources conservation (water and electricity) not only results in commercial savings, it also reduces environmental impacts with lower carbon emission.

3.7. ANN control system implementation for industrial-scale UF systems

Water reduction or recovery control in water and waste water treatment systems is a research field pursued by many researchers (Abd El-Salam and El-Naggar, 2010; Manouchehri and Kargari, 2017; Wanjiru and Xia, 2018). This UF experimental study on the advanced control system using ANN model and controllers have indicated possibility of reducing water losses compared with the conventional set-point control system. These positive results pave the way for future research implementation on industrial-scale UF membrane water treatment systems. The ANN control system could be integrated as a part of the overall operation system of industrial-scale UF membrane water treatment systems which consist of many other control components.

Various membrane fouling models (Shirazi et al., 2010; Arkhangelsky et al., 2011; Guo et al., 2012) have been suggested which have emphasized that feed water characteristics play an important role in the fouling mechanism. In this research study, it was assumed that the membrane was thoroughly cleaned without any irreversible fouling after the backwash sequences. Development of an accurate membrane fouling model increases the complexity of the control system significantly. Most end-users prefer simple models or control systems that perform adequately over complex models that describe the processes in excessive details (Lamnabhi-Lagarrigue et al., 2017). Re-training of all the ANN model and controllers once every few weeks are deemed necessary to allow the system to recognize the irreversible membrane fouling current conditions.

The ANN control system allows a more efficient operation of the dead-end constant flux UF process by regulating the duration of the filtration sequence in accordance to the feed water characteristics. This control system prolongs the filtration sequence for feed water with low turbidity until it reaches a recommended potential membrane fouling propensity (αc_s) to reduce overall water losses during the intermittent backwash sequence. During the backwash sequence, ANN controller No. 2 would ensure a thorough removal of the cake fouling layer by analysing on-line data (TMP_{rev} and V_{bw}). The combine actions of controlling the acceptable membrane fouling propensity and providing thorough backwash sequences mitigate the irreversible fouling of the membrane and prolonging the service lifetime of the membrane.

In this research study, the potential membrane fouling propensity represented by the product of αc_s was controlled within a recommended value. Under such circumstances the rate of irreversible fouling is kept within the desired level before a more rigorous and effective chemical cleaning (Levitsky et al., 2011) on the membrane is necessary. The membrane service lifetime is related to the exposure frequency and concentration of the cleaning chemicals (Ujihara et al., 2016). It was shown that using the ANN control system allows a thorough cleaning of the membrane since the potential membrane fouling propensity (αc_s) was controlled within an acceptable level before the backwash sequence. This would ensure minimal chemical cleaning is required on the membrane and the recommended lifetime of the membrane is reached or exceeded before any membrane replacement is necessary.

4. Conclusions

An advanced control system utilizing ANN model and controllers has been developed for the constant flux dead-end UF water treatment process. Detailed comparison was made between the conventional set-points and ANN control systems performance on an UF experimental system with river water. The ANN control system developed in this research was capable of reducing water losses for feed water samples with low turbidity. This control system takes into consideration the potential membrane fouling propensity of the feed water to determine the filtration durations. Such alternative process control system would be of interest to the operators of industrial-scale UF membrane water treatment plants who are interested to reduce water losses.

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Nomenclature

α	Specific cake resistance
c_s	Feed water solids concentration
V_{bw}	Total volume of water utilized during backwash
ΔP	Trans-membrane pressure
μ	Filtrate viscosity
R_m	Membrane resistance
m	Cake mass per unit membrane area
J	Filtrate flux
V_s	Volume of feed water

αc_s	Potential membrane fouling propensity
A	Membrane surface area
ANN	Artificial neural networks
APHA	American Public Health Association
NTU	Nephelometric Turbidity Units
PES	Polyethersulfone
PLC	Programmable logic controllers
PVDF	Polyvinylidene fluoride
SCADA	Supervisory control and data acquisition
TMP	Trans-membrane pressure
TMP_{rev}	Reverse trans-membrane pressure
UF	Ultrafiltration
USD	United States Dollar

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