## EVALUATION, MODELLING AND CONTROL OF ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEMS

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FACULTY OF ENGINEERING UNIVERSITY OF MALAYA KUALA LUMPUR

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### EVALUATION, MODELLING AND CONTROL OF ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEMS

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### UNIVERSITY OF MALAYA ORIGINAL LITERARY WORK DECLARATION

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Title of Thesis ("this Work"): EVALUATION, MODELLING AND CONTROL OF

# ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEMS

Field of Study: PROCESS SYSTEMS ENGINEERING AND CONTROL

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#### ABSTRACT

Ultrafiltration (UF) membrane water treatment systems are swiftly gaining acceptance for large-scale production of potable/drinking water supply in Malaysia. In the first part of this research, extensive efforts have been taken to analyze and evaluate an industrial-scale UF membrane water treatment plant in Malaysia through detailed case studies. Analysis of the UF membrane water treatment plant was performed to highlight the common design and operational issues with suggested solutions obtained from literature. Subsequently, evaluation and comparison between the UF membrane water treatment system and the conventional media/sand filtration water treatment system was conducted. Detailed analyses on commercial, quality and environmental aspects were examined on both water treatment systems. Capital costs of the UF system was 5.6% higher while the operational cost was more than three times than the conventional media/sand filtration water treatment system. Apparent advantages of the UF system were exhibited through its production of consistent filtrate turbidity of less than 1 Nephelometric Turbidity Units (NTU) and non-hazardous sludge as by-products. The sludge from the conventional system contains 58 mg/L of Aluminium residual originates from the Aluminium Chlorohydrate (ACH) utilized as coagulant in the process. Considerable efforts were also made to elucidate the key issues of scaling-up industrial-scale UF membrane water treatment system from data obtained through laboratory and pilot-scale experiments. Results have indicated that all three UF systems (laboratory-scale, pilot-scale and industrial-scale) have exhibited similar transmembrane pressure (TMP) profiles pattern under same operational conditions.

In the second part of this research work, a pilot-scale UF system has been utilized to gather data for the process modelling. A practical hybrid model which encompassed the theoretical model of Darcy's law and artificial neural networks (ANN) predictive model has been developed. This hybrid model utilizes data from commonly available on-line monitoring analyzers and laboratory analysis data in a typical UF membrane water treatment plant. Results have indicated close agreement between the simulated model and experimental data on feed water with turbidity of 10 NTU and 20 NTU respectively.

In the final part of this research work, an UF experimental system equipped with supervisory control and data acquisition software has been commissioned to implement various on-line control systems. The predictive model developed earlier has been utilized together with ANN controllers to provide an alternative control system for the dead-end constant flux UF process. Experiments were conducted to compare the results from both the ANN and conventional set-points control systems. The ANN control system has exhibited capability to reduce water losses to 4.9 % compared to the conventional set-points control system of 9.6% while maintaining acceptable potential membrane fouling propensity for low turbidity of feed water. Main objectives of this research are to demonstrate the feasible utilization of UF membrane water treatment systems and viable suggestions to improve its operations. The major contributions of this research were highlighted through case studies evaluation of the UF membrane water treatment systems, development of hybrid model for potential membrane fouling proposed alternative ANN process control system to reduce water losses.

#### ABSTRAK

Sistem rawatan air membran ultrafiltrasi telah mendapat sambutan yang amat menggalakkan sebagai teknologi pemprosesan air minum secara skala-besar di Malaysia. Dalam bahagian pertama penyelidikan ini, analisa dan penilaian secara mendalam telah diusahakan ke atas sebuah loji rawatan air membran ultrafiltrasi skalaindustri di Malaysia melalui kajian kes yang terperinci. Analisa terhadap loji rawatan air membran ultrafiltrasi skala-industri ini telah dijalankan untuk mengetengahkan isu umum dalam reakabentuk dan operasi loji dengan cadangan penyelesaian yang diperolehi daripada laporan kajian. Seterusnya, penilaian dan perbandingan di antara sistem membran ultrafiltrasi dan rawatan penapisan media/pasir yang lazim telah dilaksanakan. Analisa secara terperinci dalam aspek komersial, kualiti dan persekitaran telah dikaji ke atas kedua-dua sistem rawatan air. Kos modal untuk sistem ultrafiltrasi adalah 5.6% lebih tinggi sementara kos operasi adalah lebih tiga kali ganda daripada sistem penapisan media/pasir yang lazim. Kelebihan yang jelas sistem ultrafiltrasi adalah dalam pengeluaran tapisan dengan kekeruhan di bawah 1 NTU secara bereterusan dan penghasilan enap cemar yang tidak berbahaya. Enap cemar daripada sistem rawatan yang lazim mengandungi 58 mg/L sisa Aluminium yang berasal daripada Aluminium Chlorohydrate (ACH) yang digunakan sebagai koagulan dalam process. Usaha mendalam juga telah dijalankan untuk menjelaskan isu utama dalam menaik taraf sistem rawatan air membran ultrafiltrasi melalui data yang diperolehi daripada makmal dan kajian skala-rintis. Hasil kajian ketiga-tiga sistem ultrafiltrasi (skala-makmal, skala-rintis dan skala-industri) telah menunjukkan corak profil tekanan trans-membran yang serupa dalam keadaan operasi yang sama.

Dalam bahagian kedua penyelidikan ini, sistem ultrafiltrasi skala-rintis telah digunakan untuk mengumpul data bagi menghasilkan model proses. Satu model hibrid praktikal yang melibatkan penggunaan model teori hukum Darcy dan model jangkaan rangkaian neural buatan telah direka. Model hibrid ini menggunakan data daripada peranti pemantauan dalam talian dan analisa makmal yang sering dijumpai di kebanyakkan loji rawatan air membran ultrafiltrasi. Hasil kajian telah menunjukkan keputusan yang hampir sama di antara model simulasi dan data eksperimen untuk air mentah dengan kekeruhan 10 NTU dan 20 NTU.

Untuk bahagian terakhir dalam penyelidikan ini, sistem ultrafiltrasi kajian eksperimen yang dilengkapi dengan perisisan kawalan penyeliaan dan perolehan data telah diuji untuk menjalankan pelbagai sistem kawalan atas talian. Model jangkaan yang telah direka sebelum ini telah digunakan dengan sistem kawalan rangkaian neural buatan untuk mewujudkan satu sistem kawalan alternatif kepada proses ultrafiltrasi haluan tamat dengan kadar aliran tetap. Eksperimen telah dijalankan untuk membandingan keputusan daripada kedua-dua sistem kawalan rangkaian neural buatan dan sistem kawalan had tetapan yang lazim. Sistem kawalan rangkaian neural buatan menunjukkan keupayaan untuk mengurangkan jumlah kehilangan air sehingga 4.9% berbanding dengan 9.6% untuk sistem kawalan had tetapan yang lazim dan memastikan tahap kecenderungan potensi sumbatan membran yang boleh diterima untuk air mentah yang mempunyai kekeruhan rendah. Objektif utama penyelidikan ini adalah untuk menunjukkan keupayaan perlaksanaan sistem rawatan air membran ultrafiltrasi dan cadangan untuk memperbaiki operasi dalam sistem ini. Sumbangan terbesar dalam kajian ini adalah mengetengahkan penilaian sistem rawatan air membrane ultrafiltrasi secara kajian kes, rekaan model hibrid untuk jangkaan parameter kecenderungan potensi sumbatan membran dan cadangan kawalan proses alternatif rangkaian neural buatan untuk mengurangkan kehilangan air.

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### LIST OF SYMBOLS AND ABBREVIATIONS

W	:	Electricity power requirement (Watt)
Н	:	Pressure of the system (Pascal)
μ	:	Filtrate viscosity (kg m <sup>-1</sup> s <sup>-1</sup> )
m	:	Cake mass per unit membrane area (kg m <sup>-2</sup> )
J	:	Filtration flux (m s <sup>-1</sup> )
$\Delta P$	:	Trans-membrane pressure (Pascal)
$R_m$	:	Membrane resistance (m <sup>-1</sup> )
Q	:	Operating flowrate (m <sup>3</sup> s <sup>-1</sup> )
Jw	:	Filtration flux for purified water (m s <sup>-1</sup> )
$\Delta P_{W}$	:	Trans-membrane pressure for purified water (Pascal)
α	:	Specific cake resistance (m kg <sup>-1</sup> )
$C_S$	:	Feed water solids concentration (kg m <sup>-3</sup> )
$V_s$	:	Volume of feed water (m <sup>3</sup> )
$V_{bw}$	:	Volume of clean water utilized during backwash (m <sup>3</sup> )
$K_{sp}$	:	Solubility product
$T_{fil}$	:	Estimated filtration duration (s)
$TMP_{ol}$	:	On-line trans-membrane pressure reading (Pascal)
TMP <sub>rev</sub>	:	On-line reverse trans-membrane pressure reading (Pascal)
A	:	Membrane surface area (m <sup>2</sup> )
ACH	:	Aluminium Chlorohydrate
ANN	:	Artificial neural networks
APHA	:	American Public Health Association
ATR-FTIR	:	Attenuated total reflectance Fourier transform infrared spectroscopy
CAPEX	:	Capital expenditure
CEB	:	Chemical enhanced backwash
CIP	:	Clean in place
COD	:	Chemical oxygen demand
DOC	:	Dissolved organic carbon
EDX	:	Energy dispersive X-ray analysis
GA	:	Genetic algorithm
GUI	:	Graphical user's interface

MEUF	:	Micellar-enhanced ultrafiltration
MLD	:	Million liters a day
МОН	:	Ministry of Health Malaysia
mPES	:	Modified Polyethersulfone
MSE	:	Mean squared errors
MWCO	:	Molecular weight cut-off
NIPS	:	Non-solvent induced phase separation
NOM	:	Natural organic matter
NTU	:	Nephelometric Turbidity Units
OPEX	:	Operational expenditure
P&ID	:	Process and instrumentation diagram
PES	:	Polyethersulfone
PLC	:	Programmable logic controller
PVDF	:	Polyvinylidene fluoride
ROI	:	Return of investment
RO	:	Reverse osmosis
SCADA	:	Supervisory control and data acquisition
SEM	:	Scanning electron microscopy
TIPS	:	Thermally induced phase separation
TMP	:	Trans-membrane pressure
TSS	:	Total suspended solids
UF	:	Ultrafiltration
USD	:	United States Dollar
VSD	÷	Variable speed drive
WHO	:	World Health Organization

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#### **CHAPTER 1: GENERAL INTRODUCTION**

As the global human population reaches a new high of 7.4 billion in 2016, there is a pressing demand for more potable/drinking water supply. Technology advancement in water purification has allowed consumers to enjoy clean water supply through publicpiped networks. Large-scale water treatment plants are built to produce high volume of potable water from various raw water sources such as rivers. Membrane technology such as ultrafiltration (UF) is making headways in the water treatment industry due to its many advantages. The following sections in this chapter provide a concise introduction of this research topic on UF membrane water treatment systems and the objectives of this study.

#### 1.1 Background of study

In recent years, Malaysia has been plagued by public-piped water supply crisis both in terms of poor quality and insufficient quantity particularly in urban areas. Besides seeking for more raw water sources, advanced water treatment facilities are deemed necessary as it is one of the key focused areas in the 11<sup>th</sup> Malaysia Plan for "strengthening infrastructure to support economic expansion". Conventional water treatment processes might not be able to cope with the constant demand for higher quantity and more stringent drinking water quality (Makungo et al., 2011). Membrane technologies particularly UF has gained wide acceptance in large-scale drinking water production in many developed countries (Mierzwa et al., 2012). The adoptions of UF for drinking water production in these countries have indicated the feasibility and maturity of the technology. UF membrane technology has vast potential in the growing water treatment industry of developing Southeast Asian countries such as Malaysia.

Majority of the government-owned water treatment facilities/plants in Malaysia are utilizing conventional treatment processes (Ab Razak et al., 2015). These treatment plants often face operational issues which are caused by the fluctuation of surface raw water characteristics (Davies & Mazumder, 2003). This scenario poses an immense challenge to the operators of water treatment plants as the final treated water quality should always comply with the drinking water specification stipulated by the Ministry of Health Malaysia (MOH) and World Health Organization (WHO) (Ab Razak et al., 2016). In the conventional water treatment systems, the initial coagulation-flocculation process requires precise chemical dosage and pH adjustment to yield satisfactory solidliquid separation in the subsequent clarification and media/sand filtration processes (Zhao et al., 2014). The current pollution level caused by human activities and unpredictable weather conditions has caused surface raw water characteristics to change more often and requires frequent adjustment of chemical dosage (Mitrouli et al., 2008). This is the main drawback of the conventional water treatment systems which disrupt the smooth operation of the systems to produce consistent filtrate quality.

UF has been seen as a more reliable technology than the conventional media/sand filtration process to achieve proper solid-liquid separation results (Tian et al., 2013a). The UF process operates based on surface/cake filtration concept and does not require an initial coagulation-flocculation process prior to filtration. Industrial-scale UF membrane water treatment plant has reported very consistent high quality of filtrate during operation (Xiao et al., 2012).

#### **1.2** Scope of this research

This work focused on the evaluation of UF membrane water treatment systems and the development of a hybrid model as well as control system for the process. All the case studies in this study were based on an industrial-scale UF membrane water treatment plant located in Malaysia. Detailed evaluation of the operational data and laboratory analysis were conducted under these case studies. The hybrid model and the artificial neural networks (ANN) control system in this study were developed using mathematical computer simulation software. UF experimental systems (laboratory-scale and pilot-scale) have been designed and commissioned to conduct all the relevant filtration experiments. Natural river water was used as feed water to the UF experimental systems. Various on-line process control experiments were conducted using the UF experimental system to collect the required data. The overall scope of this research encompasses case studies, development of process model and control system for the UF membrane water treatment systems.

#### **1.3 Problems statement**

The major drawbacks of UF systems are membrane fouling (El-Abbassi et al., 2014; Filloux et al., 2012; Shirazi et al., 2010; Wang et al., 2014; Xiarchos et al., 2003) and higher overall cost compared to the conventional systems (Barello et al., 2014; Massé et al., 2011). These problems have received tremendous attention from researchers and engineers to improve the efficiency of UF systems. Identifying the root causes of such problems are the keys towards developing effective solutions. There is a lack of actual case studies on industrial-scale UF membrane water treatment systems in Malaysia reported in literature to evaluate its performance. Comprehensive evaluations and case studies of UF systems provide essential information to further highlight the challenges and substantiate the feasibility of such water treatment systems to accommodate future requirements. The common problems identified from these evaluations lead to detailed analysis of possible solutions from various literature sources.

Increasing the process efficiency by reducing resources utilizations and losses are rigorously pursued by engineers to ensure feasibility of the UF membrane water treatment systems. The procedures to analyze potential membrane fouling conditions typically required competent staff with advanced laboratory equipment. Most industrialscale UF membrane water treatment plants have limited facilities and resources in their own in-house laboratory to conduct analysis. There is a lack of practical predictive models suitable for implementation at these water treatment plants to detect potential membrane fouling conditions due to feed water characteristics changes. A more comprehensive process control system could be devised together with the predictive models to enhance the efficiency of the UF process. This research work intends to provide detailed evaluation studies and highlight the practical solutions through process modelling and control of UF membrane water treatment systems.

#### 1.4 Aim and objectives

This research aims at evaluating technical issues of UF membrane water treatment systems and suggesting solutions to the problems statement mentioned earlier. Detailed analysis and experimental works have been implemented to justify the research findings. All these efforts have been executed to achieve the objectives of this research study on UF membrane water treatment systems. There are five major objectives in this research work stated as follows:-

- 1. To highlight the design and operational issues of an industrial-scale UF membrane water treatment plant.
- 2. To evaluate and compare both the UF and conventional water treatment systems on various commercial, quality and environmental aspects.
- 3. To evaluate key issues to scale-up the UF systems from laboratory-scale and pilot-scale systems results.
- 4. To develop a practical hybrid model for the prediction of potential membrane fouling parameters in UF membrane water treatment systems.
- To develop an efficient ANN control system for the dead-end constant flux UF membrane water treatment systems.

Detailed analysis and experimental works were designed to achieve the five objectives relating to the UF membrane water treatment systems of this research work.

#### **1.5 Outline of the thesis**

This thesis is presented in the article style format which consists of eight chapters. First two chapters provide a general introduction and literature review on the research topic. The following five chapters address each objectives and finally the conclusions in the last chapter.

#### **CHAPTER 1: GENERAL INTRODUCTION**

This chapter provides an introduction of the research topic on UF membrane water treatment systems, problems statement and the main objectives of this research.

#### **CHAPTER 2: LITERATURE REVIEW**

Under this chapter, information from various sources has been gathered to produce an overall literature review which highlights relevant aspects of the UF process.

## CHAPTER 3: ANALYSIS OF INDUSTRIAL-SCALE ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM

Chapter 3 presents a case study of an industrial-scale UF membrane water treatment plant located at Kelantan, Malaysia. Issues related to feed water characteristics, membrane surface area, fouling, chemicals cleaning, hydraulic backwash efficiency and energy consumption of the UF membrane water treatment plant have been further elaborated in this chapter.

## CHAPTER 4: EVALUATION AND COMPARISON OF ULTRAFILTRATION AND CONVENTIONAL WATER TREATMENT SYSTEMS

This chapter highlights the case study of a detailed evaluation and comparison on both the industrial-scale UF and conventional media/sand filtration water treatment systems. Five aspects of comparison have been presented in this study which includes capital cost, operational cost, maintenance cost, analysis of filtrate quality and the overall water losses.

## CHAPTER 5: KEY ISSUES OF ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM SCALE-UP FROM LABORATORY AND PILOT-SCALE EXPERIMENTAL RESULTS

Chapter 5 presents a case study on three UF systems with different capacities to represent laboratory-scale, pilot-scale and industrial-scale systems. The three UF systems were compared in operational aspects such as filtrate quality, trans-membrane pressure of membrane modules and the electricity utilization.

## CHAPTER 6: POTENTIAL MEMBRANE FOULING PARAMETERS PREDICTION USING HYBRID MODELLING FOR ULTRAFILTRATION MEMBRANE WATER TREAMENT SYSTEM

This chapter presents a practical hybrid modelling approach with consists of an ANN model and a theoretical first principle model using Darcy's law. The development and results of this hybrid model has been further elaborated with experimental data in this chapter.

## CHAPTER 7: ARTIFICIAL NEURAL NETWORKS CONTROL FOR ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM

Chapter 7 highlights an alternative process control system utilizing ANN model and controllers to reduce water losses. Comparisons between this control system and the conventional set-points control system have been conducted with on-line experiments with an UF experimental system.

### **CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS**

In this final chapter, summary findings of this research work and conclusions have been highlighted. Recommendations for future studies relevant to this research have also been suggested.

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#### **CHAPTER 2: LITERATURE REVIEW**

The main research topic discussed in this work is related to the UF process of natural surface water to produce potable/drinking water. Information from various sources was gathered and a detailed literature review has been conducted to highlight the various aspects of UF membrane water treatment systems of this research. Throughout this chapter, relevant information is further elaborated and critical assessment has been presented on the overall literature findings of the UF process.

#### 2.1 Introduction

Membrane filtration systems are becoming significantly important in various solidliquid separation processes. One of the main applications of membrane filtration systems is in the water treatment industry particularly in large-scale potable/drinking water production. UF is one of the most commonly utilized membrane filtration systems in the water treatment industry due to its various advantages. There are common perceptions that membrane filtration systems for water treatment are "expensive" technologies which required high capital and operational costs. Common technical complications such as membrane fouling issues are rigorously researched and reported in various literature sources. UF membrane applications in potable/drinking water treatment systems are consistently receiving positive feedbacks. In the following sections of this chapter, various aspects of the UF systems related to water treatment have been further elaborated in details. Commonly encountered technical terms in UF membrane systems such as hollow fibre, foulant, dead-end filtration and cross-flow filtration are also further elaborated.

#### 2.2 Ultrafiltration membranes for drinking water treatment systems

Most water treatment plants are infrastructure or facilities administered by government of local authorities to provide safe potable/drinking water to the people through public-piped water supply (Marzouk & Elkadi, 2016). In Malaysia, 99% water supply for domestic use originates from natural surface water while the balance 1% of the supply comes from groundwater (Ab Razak et al., 2015). Raw water sources for water treatment plants primarily consists of freshwater inflow such as surface river water (Davies & Mazumder, 2003). One of the main solid-liquid separation process in water treatment plants is filtration (Zouboulis et al., 2007). The two most commonly used filtration systems in full-scale water treatment plants are sand/media and membrane filters. In recent years, membrane filtration systems including UF have garnered a lot of attention from researchers and engineers on its feasibility in water purification.

UF process utilizes semi-permeable synthetic membranes (commonly known as either polymeric or ceramic membranes) which are capable of segregating fine particles, bacteria and viruses from the filtrate to produce water which is safe for human consumption (Di Zio et al., 2005). The past decades of technology advancement have promoted descending membrane fabrication cost due to mass production, competitive pricing from manufacturers and the spur of demands for membrane systems (Suárez et al., 2015). Polymeric membranes are more commonly used in the water treatment industries because of its lower cost compared to ceramic membranes (Fujioka et al., 2014). Polyethersulfone (PES) and Polyvinylidene fluoride (PVDF) are some of the most widely used polymeric UF membrane in water treatment (Jalali et al., 2016; Wang et al., 2016b). Polymeric membranes are commonly fabricated using either non-solvent induced phase separation (NIPS) or thermally induced phase separation (TIPS) methods (Jung et al., 2016).

Membrane technology is applied in various formats such as hollow fibre, tubular, flat plate, spiral, stirred cell and rotating. The most commonly used format for water treatment is the hollow fibre system due to its high specific packing density (Arndt et al., 2016). The hollow fibre membranes are usually contained in cylindrical shaped pressure housing and collectively known as membrane modules. Figure 2.1 shows the UF hollow fibre membrane module produced by Inge GmbH from Germany and its cross-sectional view. These membrane modules usually consist of proprietary design developed and produced by the membrane manufactures to suit the application of their membrane (Wan et al., 2017).



Figure 2.1: UF hollow fibre membrane module produced by Inge GmbH (Germany) and its cross-sectional view

There are two common operation modes for UF membranes applied on industrialscale systems which are dead-end and cross-flow filtrations (Mota et al., 2002). Among these operation modes, dead-end filtration is more desirable for industrial-scale UF membrane water treatment plants because of its lower specific energy requirement (kWh/m<sup>3</sup>) compared to cross-flow filtration (Mendret et al., 2009). The dead-end filtration operation requires an intermittent backwash to be carried out as physical cleaning after each filtration sequence. Cross-flow filtration is a continuous operation process whereby both filtrate and concentrate (sludge) streams are produced simultaneously. Figure 2.2 illustrate the dead-end and cross-flow filtration operation modes.



Figure 2.2: Dead-end and cross-flow filtration operation modes

UF is utilized in water treatment plants to ensure high efficiency of solid-liquid, bacteria and viruses separation in order to achieve potable/drinking water standards (Besmer & Hammes, 2016). Pore size of the UF membrane plays a major role for the separation process and reported to fall within 35 - 20 nm for water treatment applications (Akhondi et al., 2017). The pore size of the UF membrane is a complex and important characteristic of the membrane (Arkhangelsky et al., 2012).

#### 2.3 Analysis and evaluation of UF membrane water treatment systems

In-depth understanding of the difficulties encountered in UF membrane water treatment systems enables the possibilities for viable solutions on membrane fouling and other operational issues. In order to highlight the technical problems encountered in UF systems, case studies on industrial-scale systems were highly recommended for detailed analysis (Petrinic et al., 2015; Vera et al., 2017; Xiao et al., 2012). Some of the most common issues in membrane systems are the irreversible fouling of the membranes (Guo et al., 2012; Shirazi et al., 2010; Thekkedath et al., 2007; Wang et al., 2014) and the higher cost of operation compared to the conventional media/sand filtration systems (Massé et al., 2011). Membrane fouling is defined as depositions of unwanted and non-integral substances known as foulant on the membrane surface which causes undesirable consequences and additional resistance (Ho et al., 2016; Porcelli & Judd, 2010).

In recent years, many researchers have conducted laboratory analyses on membrane fouling mechanism to determine the causes which eventually might leads to feasible solutions for the cleaning procedures (Arkhangelsky et al., 2011; Sioutopoulos & Karabelas, 2012; Stoller et al., 2013; Tian et al., 2013a; Xiao et al., 2012). These analyses provided more insights and hypotheses on the causes of such problems encountered in UF membrane systems particularly in water treatment under laboratory controlled environment. Case study of an actual system would allow a much rigorous investigation protocol to be implemented and provides much reliable results (Arroyo et al., 2016).

Besides laboratory-scale analyses, experiments on pilot-scale UF membrane systems were also reported in literature to provide much precise information (Arnal et al., 2008b; Arnal et al., 2007). These pilot-scale studies are usually conducted over a prolong period of time (ranges from a few weeks to a few months) which could yield results which have much closer approximation to a full-scale system. Laboratory experiments and pilot-scale studies are preliminary evaluation methods to analyze the effect of the feed water on particular types of industrial-scale UF membrane systems (Bu-Rashid & Czolkoss, 2007; Glueckstern et al., 2000; Halpern et al., 2005; Rajca, 2016). These laboratory-scale and pilot-scale UF systems are distinctively smaller size than industrial-scale systems but they should retain the same type of UF membrane (produced by the same manufacturer) to ensure similar characteristics. Figure 2.3 indicates the example of various sizes and membrane surface area contained in each type of UF membrane modules (produced by the same manufacturer) for the laboratory-scale, pilot-scale and industrial-scale systems.



Laboratory-scale UF module with  $1.0 \text{ m}^2$  membrane surface area

Pilot-scale UF module with  $6.0 \text{ m}^2$  membrane surface area

Industrial-scale UF module with  $60 \text{ m}^2$  membrane surface area

Figure 2.3: Various sizes and membrane surface area of UF membrane modules produced by Inge GmbH (Germany)

Case studies involving industrial-scale systems are commonly utilized to evaluate and demonstrate the capabilities of certain processes or systems (Altuntas et al., 2016; Marshall et al., 2016; Pitkänen et al., 2016). Various researchers have conducted case studies on industrial-scale water treatment systems in recent years to demonstrate the relation to economic and environmental impacts (Tornevi et al., 2016; Walsh et al., 2017; Weidhaas et al., 2017). These case studies were relevant towards specific locations from where the data were obtained and might not be accurate to represent some other locations. There are not many case studies in Malaysia related to industrialscale UF membrane water treatment systems reported in literature mainly because conventional media/sand filtration is still dominant in most industrial-scale water treatment systems.

#### 2.4 Modelling of UF membrane filtration process

Process modelling is a fundamental method to understand or estimate how the input parameters of a process affect the outputs (Al-Obaidi et al., 2017). Membrane filtration processes are swiftly gaining acceptance as mainstream solid-liquid separation methods and the modelling of membrane filtration pose a significant importance to optimize the operation and address the membrane fouling problems (Llanos et al., 2013). Fundamental models of solid-liquid membrane filtration have been developed by researchers and these models were validated through laboratory experiments (Kim & DiGiano, 2009; Tien et al., 2014). These researchers applied the Darcy's law to establish correlation between flux, resistance and pressure in their models. According to the Darcy's equation, a cake layer of fine solids formed on the upstream membrane surface causes resistance to the liquid molecules and raises the trans-membrane pressure (TMP) of the filtration process (Osterroth et al., 2016). The TMP is proportional to the resistance of the fouling layer under constant flux filtration conditions (Oishi et al., 2015). A commonly accepted definition of TMP is the pressure drop across the membrane barrier typically measured through the inlet and filtrate ports of the membrane (Boyd & Duranceau, 2013).

The cake layer permeability is an important parameter which affects the filtration process substantially. Permeability of a UF membrane filtration system is defined as the filtration flux at a given TMP (Lee & Park, 2016). Under constant flux filtration, the cake layer permeability decreases over time due to the accumulation of higher solids concentrations on the membrane surface. In order to maintain constant flux filtration, the feed water pressure would need to be increased to overcome the higher TMP. Membrane filtration at high TMP increases the electricity power requirement which translates to higher operational cost. Various membrane cleaning methods are often implemented to reduce the TMP.

One of the main obstacles to predict the cake layer permeability arises due to the difficulty in estimating the average, effective, particle size present in the feed water. High-end laboratory analysis equipment or methods such as scanning electron microscopy (SEM), energy dispersive X-ray analysis (EDX) and attenuated total reflectance Fourier transform infrared spectroscopy (ATR-FTIR) were often used to analyze the chemical composition of membrane surface, size and shape factor distribution of the solid particles attached on the membrane surface (Bourcier et al., 2016; Marbelia et al., 2016). These expensive and high-end laboratory equipment for analysis procedures are seldom available in large-scale membrane water treatment plants and usually these analyses are conducted by third party specialist laboratories. Figure 2.4 illustrates the formation of fine solids cake layer on the UF membrane surface.


Figure 2.4: A cake layer membrane filtration model

Under ideal laboratory conditions, the feed solution/water should have fixed concentration of the suspended solids with similar particle size so that the cake layer could be uniformly developed (Sioutopoulos & Karabelas, 2012; Tian et al., 2013b; Yi et al., 2013). A typical industrial-scale UF membrane water treatment plant rarely has such ideal feed water as the surface water is subjected to weather condition such as heavy rain falls and surface run-off which changes the suspended solids concentration drastically. Most feed water sources to water treatment plants originates from freshwater inflow such as river water (Davies & Mazumder, 2003). Various pre-treatment processes such as chemical coagulation-flocculation prior to UF are often implemented to reduce the impact of feed water characteristic changes on the membrane filtration (Tian et al., 2013c; Wei et al., 2016; Yu & Graham, 2015). All pre-treatment processes

incurred additional cost and equipment to facilitate the systems which might not be feasible for some water treatment plants.

Modelling of an actual membrane filtration system poses many challenges (Li et al., 2016a). The significant variation and changes of the feed water characteristics mentioned earlier would require certain parameters of the model to be changed as well. There are three common methods of modelling a process reported in literature which are known as the white-box model, black-box model and grey-box model (Afram & Janabi-Sharifi, 2015). The complexity level of the process determines which modelling method is more suitable. In UF systems, the grey-box model or hybrid model has been utilized to predict the TMP of the process with much higher accuracy than the white-box or physical model (Liu et al., 2016). Hybrid models have the advantage of combining both the white-box and black-box models characteristics to yield a much accurate results in some processes. Table 2.1 shows the characteristics of the three commonly utilized modelling methods.

White-box model	Black-box model	Grey-box model
<ul> <li>understanding of the system physics</li> <li>using the required parameters to model the system dynamics</li> <li>good generalization capabilities but poor accuracy in some systems</li> </ul>	<ul> <li>little or no understanding of the system is required</li> <li>using regression method to fit the inputs and outputs data with mathematical function.</li> <li>poor generalization but high accuracy in some systems</li> </ul>	<ul> <li>partial combinations of the white-box and black-box model</li> <li>use the physics based model as the mathematical structure</li> <li>measured inputs and outputs data to estimate parameters of the model</li> <li>acceptable level of generalization and accuracy for some systems</li> </ul>

Table 2.1: Characteristics of commonly used modelling methods

# 2.5 Process control and fouling of UF membrane water treatment systems

UF membrane fouling is the most critical problem that many researchers have tried to overcome (Guo et al., 2012). Various methods to reduce membrane fouling such as physical cleaning, membrane surface modification and others hydrodynamic flushing procedures to dislodge the attached solids on the membrane surface have been suggested (Aslam et al., 2017; Shamsuddin et al., 2015). A typical definition of membrane cleaning is a set of procedures applied to relieve non-integral substance which are also known as foulant from the membrane surface (Porcelli & Judd, 2010). Hydraulic backwash is a type of physical cleaning method widely applied in UF membrane water treatment systems to reduce irreversible fouling (Chang et al., 2015). Under the dead-end operation mode, intermittent backwash is carried out after each filtration sequence to clean the membrane from foulant (Mendret et al., 2009). The backwash sequence has been acknowledged to decrease membrane pore and cake fouling to improve the filtration flux (Akhondi et al., 2017).

Another important factor defining the performance of membrane systems is to ensure high recovery rate and reduce water losses (Zhang et al., 2017). Rigorous studies on effective backwash methods of UF systems were investigated by various researchers (Chang et al., 2016a; Chang et al., 2016b; Chang et al., 2015). Effective process control of the backwash process in UF systems is the key element to mitigate membrane fouling (Gu et al., 2016). Most of the municipal and industrial-scale membrane water treatment plants implement fixed durations of filtration and backwash sequences based on membrane manufacturer and the design engineers recommendations (Cogan & Chellam, 2014). The process control logic sequences are normally programmed based on predetermined set-points (Alphonsus & Abdullah, 2016). This might not provide the most effective process control as external factors such as feed water characteristic changes have not been taken into considerations. Optimizing the operating conditions of the membrane filtration and backwash processes could mitigate membrane fouling (Shi et al., 2014). Process control plays an important role to ensure the products/outputs quality and minimized the resources required for the system (Foscoliano et al., 2016). Most large-scale water treatment plants utilized natural surface water such as river as feed water (Davies & Mazumder, 2003). The natural feed water consists of various particles and matrix of organic matter which were known as organic foulants for membranes (Shang et al., 2015). In order to ensure smooth and efficient membrane systems operation, various process control strategies have been proposed by researchers (Córdova et al., 2016; Gao et al., 2016; Gu et al., 2016). These were very specific process control strategies catered for certain processes and objectives. Table 2.2 summarized some of the researchers work in process control strategies or objectives for UF processes.

Researchers	Descriptions
(Gu et al., 2016)	Using continuous pulse backwash control for UF system. Implemented self-adaptive triggering of UF backwash which increases the consecutive pulses when a higher membrane fouling resistance was detected.
(Gao et al., 2016)	Introduced the concept of using concentrate from reverse osmosis (RO) system for UF backwash. This allows high recovery of the UF system by implementing flexible backwash strategies.
(Córdova et al., 2016)	Detailed study on UF membrane bioreactor operational conditions. Analyses of the fouling mechanism which allow more understanding on the impact of various parameters.
(Tian et al., 2013c)	Using pre-oxidation and coagulation for UF membrane fouling control. By dosing a combination of $KMnO_4$ and $FeCl_3$ in the feed water, the total fouling resistance of the membrane decreases.
(Bai et al., 2015)	Applying surface modification techniques to improve antifouling properties of the UF membrane. The modified membrane shown excellent performance on natural organic matter fouling control in this work.

Table 2.2: Literature reports on process control of UF systems

Most of the process controls for UF water treatment systems are aimed at enhancing the efficiency of the process. Reducing the energy/electricity and water losses are some of the major achievements of high efficiency process control for UF systems. Both of these aspects (energy and water losses) are inter-related as membrane fouling causes higher TMP which requires more energy to drive the feed pump and higher water volume to clean the membrane. Ensuring minimal or acceptable UF membrane fouling is the key element to achieve efficient process control in the long term.

# 2.6 Summary of overall literature review

Literature research findings reported on UF has indicated its feasibility for commercialization in water treatment systems. The dead-end filtration operation mode is a more efficient process for industrial-scale UF membrane water treatment plants which could potentially lowered down operational cost. Detailed analysis of the UF membrane fouling model enables a better control strategy to be developed on the process. Main objectives of this research are to highlight some of the important aspects of industrial-scale UF membrane water treatment systems through case studies and propose practical modelling as well as process control approach to mitigate some of the problems.

#### **CHAPTER 3:**

# ANALYSIS OF INDUSTRIAL-SCALE ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM

The average household water tariff (denoted in United States Dollar or USD) in Malaysia (0.39 USD/m<sup>3</sup>) is among the lowest in Southeast Asia region compared with neighboring countries such as Indonesia (0.77 USD/m<sup>3</sup>) and Singapore (1.88 USD/m<sup>3</sup>) (Lee et al., 2016b). One of the reasons is because most of the industrial-scale water treatment plants in Malaysia are still utilizing conventional media/sand filtration systems which require low capital construction and operational cost (Ab Razak et al., 2015). Developed countries in Asia such as Singapore and Japan have adopted membrane technologies over the conventional media/sand filtration in large-scale potable/drinking water treatment facilities to fulfill their countries industrial-scale water treatment plants in Malaysia and further analysis of such systems are much needed.

# 3.1 Introduction

In this chapter, a detailed case study of an industrial-scale UF membrane water treatment plant located at Kelantan, Malaysia has been highlighted. This is one of the largest government-owned UF membrane water treatment plant in the country which provides potable/drinking water to a small town through the public-piped water supply networks. Under this case study, actual operational data of the UF membrane water treatment plant was recorded and analyzed to elucidate the performance of this water treatment plant. Comparison between literature report and the actual findings from this case study was made to further elaborate the analysis. These findings would assist in bridging the gaps between literature findings and the actual difficulties encountered in an industrial-scale UF membrane system. Understanding these differences and similarities would have significant impacts and benefits to improve the operation and design of such UF membrane systems.

### 3.2 Background

In recent decades, the manufacturing cost of polymeric UF membrane has decreased significantly due to mass production. This type of UF membrane has garnered high acceptance for utilization in industrial-scale water treatment systems (Laîné et al., 2000). It was reported that UF has been considered as one of the most commonly applied alternative water treatment systems to produce drinking water in large-scale (Mierzwa et al., 2012). This conclusion arise from the fact that the UF systems are capable of substituting the entire conventional water treatment process to remove fine solids, bacteria and virus from the feed water (Tian et al., 2013a). UF systems are considered highly efficient and environmentally friendly pre-treatment technology prior to seawater desalination (Tang et al., 2016b). There are a lot of challenges in the fluctuations of inputs parameters such as feed water and difficulties to scale-up the optimum conditions from the laboratory-scale and pilot-scale systems (Zupančič et al., 2014).

One of the common methods deployed to analyze large-scale UF membrane systems are through case studies (Petrinic et al., 2015; Vera et al., 2017). Researchers have shown that an industrial-scale UF membrane water treatment plant at Nantong, China produced very consistent filtrate quality with 99% turbidity reduction and no coliform bacteria was detected (Xiao et al., 2012). These results have clearly exhibited UF capability to replace conventional water treatment system to produce safe drinking water.

Besides the membrane fouling issues, most industrial-scale UF membrane water treatment systems also faced higher overall construction and operational costs than the conventional systems (Massé et al., 2011). Drinking water production cost model correlating membrane characteristics such as strength, fouling propensity and permeability has been reported in the literature to highlight some of the commercial issues (Pearce, 2012). Even though dead-end UF operation mode is more preferable in water treatment systems (Mendret et al., 2009), it has a major disadvantage of high velocity of fine solids deposited on the membrane surface (Remize et al., 2010). One of the most promising advantage of dead-end UF operations reported is the lower energy requirement per unit of filtrate production under low TMP ranging from 0.2 to 0.8 Bar (Massé et al., 2011).

Designing efficient fouling control is one of the many challenges towards an efficient UF system operations (Shirazi et al., 2010). Laboratory experiments have shown that membrane fouling causes flux declined and increased TMP (Xiao et al., 2012). Some researchers have proposed the use of hybrid membrane process utilizing activated carbon to alleviate membrane fouling issues but encountered with other challenges such as membrane abrasion (Stoquart et al., 2012). Another effective method to restore flux decline due to membrane fouling is through specific chemical cleaning (Arkhangelsky et al., 2007; Arnal et al., 2008a; Levitsky et al., 2011). Although chemical cleaning is an effective method to remove foulant, it has the tendency to enlarge the pore structure causing deformation of the membrane material. Hydraulic backwash is a much more preferable but less rigorous membrane cleaning method to remove fouling which is

under tremendous attention by scientific researchers (Bessiere et al., 2009; Katsoufidou et al., 2008; Lipp & Baldaufb, 2002; Remize et al., 2010; Ye et al., 2011).

Limiting flux or volume of filtrate per membrane area (m<sup>3</sup>/m<sup>2</sup>hr) is also a common method to control membrane fouling and optimize the filtration operation (Field & Pearce, 2011; Zhang et al., 2016). Under normal circumstances, a lower flux correlates to a lower fouling rate and vice versa. The characteristic of the feed water has a high impact on this limiting flux. Prior to the design of a large-scale membrane system, pilotscale studies are often carried out to determine the specific flux based on the feed water characteristics (Manth et al., 1998). Design engineers are often faced with challenges in determining optimum design parameters in order to reduce the cost of membrane required and ensuring minimum membrane fouling possibilities.

All these issues related to feed water characteristics, membrane surface area, fouling, chemicals cleaning, hydraulic backwash efficiency and energy consumption of an industrial-scale UF membrane water treatment plant have been further elaborated in this research work. Data obtained from this case study water treatment plant was compared with literature findings to establish possible solutions for the problems. The subsequent sections in this chapter provide details of the analysis methodology and the findings with relevant discussions.

# **3.3** Methodology

An industrial-scale UF membrane water treatment plant located at Kelantan, Malaysia has been selected for the case study in this research. Figure 3.1 shows the actual site photo of the water treatment plant.



Figure 3.1: UF membrane water treatment plant at Kelantan, Malaysia

This water treatment plant was designed to produce up to 14 million liters a day (MLD) or 576 m<sup>3</sup>/hr of potable water commences operation since February 2013. The potable water from this treatment plant was channeled to the public-piped water supply networks. Feed water to this water treatment plant was extracted from a riverbank filtration intake and subsequently pumped to a cascading aerator. After passing through cascading aerator, further forced-aeration with mechanical blowers was carried out in an extended aerator for the oxidation of manganese and iron constituents.

Preliminary filtration process was achieved using pressurized media/sand filters before proceeding to the UF systems. Finally the filtrate was disinfected with liquid chlorine before supplying to the public-piped water supply networks. Figure 3.2 shows the flowchart of the industrial-scale UF membrane water treatment plant processes.



Figure 3.2: Flowchart of the industrial-scale UF membrane water treatment plant

This UF membrane water treatment plant implemented direct filtration without the addition of any chemical as coagulant and flocculant. The water treatment plant was designed for fully automated operation with minimal human intervention except during abnormal conditions. Most of the operational data was recorded digitally using on-line analyzers and recorders. Table 3.1 shows the on-line analyzers/sensors available for digital data monitoring in this case study.

Analyzer/Sensor	Location	Measured data		
Electromagnetic flowmeter	Feed/raw water pipeline and treated water pipeline	Flow rate of feed/raw water and treated water from the treatment plant		
Turbidity analyzer	Feed/raw water pipeline and treated water pipeline	Turbidity of the feed/raw water and treated water from the treatment plant		
Pressure transmitters UF membrane modules inlet and filtrate header pipes		Determine the trans-membrane pressure (TMP) of the UF membrane		
Electricity usage meter	Main incoming electricity supply cable	Electricity consumption of the UF membrane water treatment plant		

Table 3.1: On-line analyzers/sensors for digital data monitoring

Besides the on-line analyzers/sensors, the water treatment plant was also equipped with an in-house laboratory to conduct water quality analysis on a daily basis. All these available facilities were to ensure that the water treatment plant produces safe potable water to the public-piped supply networks. This UF membrane water treatment plant comprises 120 units of Dizzer XL 0.9 MB 60W UF membrane modules (produced by Inge GmbH, Germany) as one of the main components. The total membrane surface area of all these UF modules combined was equivalent to 7, 200 m<sup>2</sup> which have been recommended to operate at 80 L/m<sup>2</sup>hr of flux rate. These were polymeric membranes made from modified Polyethersulfone (mPES). The membranes were manufactured into strands of hollow fibre consisting of 7 capillaries of 0.9 mm diameter each. Average pore size of the membrane was approximately 0.02  $\mu$ m with molecular weight cut-off (MWCO) of about 100 kDa. Figure 3.3 shows the hollow fibre membrane and its crosssectional view.



Figure 3.3: UF hollow fibre membrane utilized at the water treatment plant

Utilizing the availability of all the facilities in this industrial-scale UF membrane water treatment plant, the relevant operational data of the system was collated and analyzed in detailed. The following sections in this chapter further elaborate on the findings and discussions.

# 3.4 Results and discussions

In this section, all the relevant operational data from the water treatment plant was compiled, analyzed critically and discussed. The analyses encompassed aspects such as membrane surface area, feed/raw water characteristics, chemicals for UF membrane cleaning, hydraulic backwash/chemical cleaning efficiency, UF membrane fouling and electricity consumption.

#### 3.4.1 Membrane surface area

The first and foremost important design parameter of UF membrane systems is to ascertain the required membrane surface area to achieve the design filtrate capacity (Manth et al., 1998). Flux rate of between 50 - 130 L/m<sup>2</sup>hr in UF water treatment systems are common and dependence on the characteristics of the feed/raw water. There are 3 common definitions of filtration fluxes reported in literature (Field & Pearce, 2011) and further elaborated in Table 3.2.

Terms	Definitions
Critical flux	Flux at which fouling is first observed at a known cross- flow velocity
Sustainable flux	Flux that is maintained by chemical and mechanical cleaning methods to ensure the desired operations cost and the membrane service life.
Threshold flux	Flux which a low and consistent rate of membrane fouling take place

Table 3.2: Definitions of various flux conditions for membrane systems

These various flux conditions have suggested laboratory experiments or pilot-scale studies should be carried out to determine the most suitable filtration flux and subsequently the required membrane surface area. This case study industrial-scale UF membrane water treatment plant was initially designed based on a few samples of the raw water from the river without going through a rigorous pilot-scale study. The incoming raw water turbidity from the river bank filtration intake was estimated to be below 20 Nephelometric Turbidity Units (NTU) and this was used as the basis for the design of the UF system. Based on this assumption, the filtration flux rate was fixed at 80 L/m<sup>2</sup>hr as the designed flux to achieve the desired maximum output of 576 m<sup>3</sup>/hr with 7, 200 m<sup>2</sup> of UF membrane surface area. The UF system was operated under deadend constant flux filtration mode with intermittent backwash. During preliminary design stage, the UF membrane's manufacturer simulation software (Inge System Design) was utilized to determine the flux rate based on feed water data such as dissolved organic carbon (DOC), temperature, chemical oxygen demand (COD), pH, turbidity and suspended solids concentration.

It is generally a known fact that membrane filtration is a complex process that involves many interacting factors which requires extensive monitoring, cost and time (Seyed Shahabadi & Reyhani, 2014). Many researchers have conducted more than 4 months of UF pilot-scale studies to determine the interacting factors for a better understanding of the systems (Holloway et al., 2015; Loganathan et al., 2016; Urgun-Demirtas et al., 2013). In many cases (such as this case study water treatment plant), these extensive pilot-scale studies were often neglected due to budget and time constraint. Operation problems such as irreversible fouling might not manifest as a major issue during the initial period of operation but rather at a much later stage. Complications arise when initial feed water characteristic assumed in the design stage significantly deviates during the actual operation of the system which has been further discussed in the subsequent sections.

#### **3.4.2 Feed/raw water characteristics**

It was mentioned earlier that most of the potable/drinking water sources originated from surface freshwater such as rivers (Davies & Mazumder, 2003). River water turbidity is highly dynamic and exhibits significant changes due to heavy rainfalls conditions (Lee et al., 2016a). Various constituents such as humic acid (Sioutopoulos & Karabelas, 2012), inorganic salts (Shirazi et al., 2010), biopolymer (Tian et al., 2013a) and heavy metal ions (Choo et al., 2005) in the feed water are potential foulant in membrane systems.

Feed water characteristics and the UF flux rate constitute inter-dependency relationship. Extreme contamination or problematic feed water with high constituents of potential foulant would necessitate low flux rate and frequent cleaning to reduce irreversible membrane fouling. River/raw water characteristics fluctuation is most commonly monitored through on-line turbidity analyzers (Marchant et al., 2015). Raw water sample turbidity is measured using optical analysis method in Nephelometric Turbidity Units (NTU). This turbidity measurement is often inferred to the suspended solids concentrations of the samples. Natural water samples with high suspended solids concentration often means having high constituents of foulant as well.

Design engineers are usually faced with the dilemma of construction cost and long term efficiency/durability of a system (Snelgrove & Saleh, 2016). In order to ensure a fair estimation of the river water characteristics, grab samples were conducted randomly within a 3 months period prior to the design of this UF membrane water treatment plant. The average analysis results indicated the river water turbidity was below 20 NTU. This information was then utilized as the design basis for the UF membrane water treatment plant which commences construction in 2011. After the treatment plant commenced commercial operation in 2013, daily feed water analyses from the same river were

conducted. Figure 3.4 shows the daily river/feed water turbidity to the water treatment plant recorded in September 2013.



Figure 3.4: Feed water turbidity to UF membrane water treatment plant

The monthly average of the feed water turbidity in September 2013 was 13.7 NTU which falls within the design limit of 20 NTU or below. A more detailed analysis indicated that there were at least 4 days (7<sup>th</sup>, 8<sup>th</sup>, 13<sup>th</sup> and 15<sup>th</sup> of September 2013) or approximately 13% of the time the feed water daily average turbidity exceeding 20 NTU with the highest reading recorded at 68 NTU.

Most of the industrial-scale automation systems including this water treatment plant were executed using programmable logic controllers (PLC) with pre-determined timers and set-points (Alphonsus & Abdullah, 2016). The control system for this water treatment plant has been programmed to operate efficiently and automatically with feed water turbidity of 20 NTU or below. On-line turbidity analyzer in this water treatment plant would trigger an alarm when the raw water turbidity exceeds 20 NTU to warn the operators. Subsequently the operators could either continue to operate the water treatment plant under the same operating conditions or totally cease operation. Since ensuring continuous potable water supply to the public-piped networks is essential to the consumers, halting operation of the water treatment plant due to high turbidity of the feed water is seldom a preferred option. Such abnormal conditions do not augur well on the UF membrane system, as mentioned earlier the higher feed water turbidity would equate to higher membrane fouling potential as well. The flux rate and membrane cleaning sequence or procedures would require readjustment to reduce the filtrate output from the water treatment plant. Most water treatment plants operate under constant flux filtration to ensure consistent water supply production (Pearce, 2007b). The water treatment plant's operator has very little choices but to continue operating at similar flux rate even though the feed water turbidity has surged up much higher than expected.

### 3.4.3 Chemicals for UF membrane cleaning

Recent developments on membrane technology focus on the cleaning procedures. One of the most extensively researched membranes cleaning method is by using chemicals to remove or dislodge foulant from the membrane surface and pores (Arkhangelsky et al., 2007; Arnal et al., 2008a; Levitsky et al., 2011; Piasecka et al., 2015; Ujihara et al., 2016; Wang et al., 2016a). Even though hydraulic cleaning such as backwash and flushing is a much preferable membrane cleaning method, the effectiveness of such cleaning was less compared to chemical cleaning (Rabuni et al., 2015). This case study UF membrane water treatment plant was utilizing two types of chemical for membrane cleaning recommended by the membrane manufacturer. According to the manufacturer, the UF membrane was compatible with three categories of feed water mainly seawater, surface/ground water and wastewater. Different types of chemicals are recommended to different categories of feed water for effective membrane cleaning.

Since the feed water to this water treatment plant originates from a natural surface river source, the membrane manufacturer has recommended Hydrochloric Acid (HCl) and Sodium Hydroxide (NaOH) for the membrane cleaning. Sodium Hypochlorite (NaOCl) is recommended for chemical cleaning if the feed water is from wastewater or seawater sources. This is due to the fact that high organic foulant is often found in such problematic waters. Although NaOCl is an effective membrane cleaning agent, it also causes membrane disintegration (Ujihara et al., 2016). Under normal circumstances most polymeric membranes are not highly resistance towards strong chemical such as NaOCl (Regula et al., 2014). NaOH and HCl are much commonly used cleaning agents for membrane cleaning with less undesirable membrane deformities. Alkaline such as NaOH is an effective chemical to remove organic foulants in PES based UF membranes (Antón et al., 2015). HCl is known as an effective acidic chemical to remove inorganic foulants on membrane pores and surface (Li et al., 2016b). This case study water treatment plant implemented what is known as chemical enhanced backwash (CEB) utilizing both NaOH and HCl separately after every 24 cycles of filtration sequences with an intermittent hydraulic backwash in between each filtration sequences. Each cycle consists of a filtration sequence which lasts for 30 minutes and subsequently a hydraulic backwash for 60 seconds. The effectiveness of the chemical cleaning and hydraulic backwash on the membrane was further discussed in the following section.

# 3.4.4 Hydraulic backwash and chemicals cleaning efficiency

Hydraulic backwash of UF membrane systems have been extensively researched and reported in literature (Bessiere et al., 2009; Katsoufidou et al., 2008; Lipp & Baldaufb,

2002; Remize et al., 2010; Ye et al., 2011). Under dead-end filtration operation mode with high solids accumulation, hydraulic backwash is conducted after each filtration sequence of between 10 - 60 minutes. Chemical enhanced backwash (CEB) cleaning is less frequent which is normally performed once between 10 - 50 cycles of continuous filtration and hydraulic backwash sequences. Nevertheless both hydraulic backwash and CEB are the most common membrane cleaning procedures. Steadily increase of feed water pressure and TMP during every subsequent filtration and hydraulic backwash sequences indicates that CEB might be necessary for a more thorough membrane cleaning. This case study water treatment plant implements a 20 minutes CEB process for each chemicals (NaOH and HCl) which includes chemical injection, soaking and rinsing. CEB is carried out to remove the foulant which was unable to be dislodged from the membrane pores and surface during the hydraulic backwash. The effectiveness of the membrane cleaning procedures could be ascertained by examining the pressure profiles during the filtration sequences. After 30 minutes of filtration sequence, a 60 seconds hydraulic backwash was initiated. This cycle of filtration and backwash was then repeated until a CEB was required. Figure 3.5 and Figure 3.6 show the feed water pressure profiles on 23/9/2013 after hydraulic backwash and CEB.



Figure 3.5: Feed water pressure profile after backwash and alkaline CEB



Figure 3.6: Feed water pressure profile after backwash and acid CEB

The hydraulic backwash only marginally reduces the feed water pressure when the following filtration sequence was initiated as shown in both Figure 3.5 and Figure 3.6. It was suggested that during a hydraulic backwash instead of removing the cake filtration layer, the layer was only being spread out and expanded from the membrane surface (Ye et al., 2011). The cake filtration layer was then recompressed during the subsequent filtration sequence resulting in minimal or insignificant reduction of the resistant pressure shown in Figure 3.5 and Figure 3.6.

A more substantial feed water pressure reduction was noticed after an alkaline (NaOH) CEB was carried out in Figure 3.5. The pressure declined by 0.2 Bar after the alkaline CEB. Alkaline chemical cleaning was proven to be effective in restoring filtration flux for PES membrane (Levitsky et al., 2012). It has also been suggested that chemical used for membrane cleaning targets specific foulant which exists in the feed water (Alzahrani et al., 2013). Alkaline chemical is effective to remove organic foulant in membrane. During alkaline CEB the UF membrane was soaked at pH of more than 12 with the NaOH solution for 20 minutes before hydraulic backwash was initiated to clean out the chemical from the membrane surface.

In Figure 3.6, the reduction of the feed water pressure of an acid CEB was even more significant than an alkaline CEB. It has recorded 0.4 Bar of pressure reduction after the acid CEB. As mentioned earlier, the effectiveness of the chemical cleaning was specific to the membrane foulant. Table 3.3 indicates a few parameters analyzed in the filtrate and feed water from the UF membrane water treatment plant.

Parameters	Feed water	UF filtrate	Removal (%)	Approved limit
Fe	0.76 mg/L	< 0.002  mg/L	> 99	< 0.3 mg/L
Mn	0.13 mg/L	< 0.002 mg/L	> 98	< 0.1 mg/L
Turbidity	68 NTU	0.15 NTU	> 99	< 5 NTU

Table 3.3 Analysis of feed water and UF filtrate

The high content of iron (Fe) and manganese (Mn) concentrations in the feed water suggested that inorganic fouling of the UF membrane was highly possible. Acid cleaning is an effective method against inorganic fouling as it dissolved the Fe and Mn into soluble ions which are flushed out during backwash (Wang et al., 2016c). The feed water pressure was reduced by 0.4 Bar after the acid CEB compared to only 0.2 Bar in the alkaline CEB. Table 3.4 indicates the effectiveness of both the alkaline and acid CEB on the UF system.

Parameters	Alkaline CEB	Acid CEB
Duration	20 minutes	20 minutes
Chemical	NaOH (pH > 12)	HCl (pH < 2.5)
Initial pressure	3.0 Bar	3.1 Bar
Pressure after CEB	2.8 Bar	2.7 Bar
Pressure difference	0.2 Bar	0.4 Bar

Table 3.4: Operational parameters of the acid and alkaline CEB

Results from Table 3.3 and Table 3.4 indicated that the effectiveness of the CEB cleaning was dependent on the type of foulant. The feed water to the water treatment plant contained high constituents of Fe and Mn concentrations which indicated great potential of inorganic membrane fouling. Acid CEB was much more effective in

removing inorganic foulant and this has alleviated the membrane fouling by reducing the feed water pressure after the chemical cleaning procedures. There are possibilities that other types of acid cleaning solutions such as citric acid, oxalic acid and sulphuric acid might perform even better than HCl to remove foulant from the membrane. Fluctuating characteristic changes of the feed water might require reassessment of the chemical used for CEB. As mentioned earlier, certain fouling would require specific cleaning chemical for effective foulant removal from the membrane.

### 3.4.5 UF membrane fouling

One of the most critical issue for industrial-scale membrane system is the membrane fouling (Shirazi et al., 2010). Membrane fouling is caused by non-integral substances or foulant from the feed water attached to the membrane and causes decline in permeability. Permeability is defined as flux rate through the membrane at a given TMP (Ma et al., 2016). Membrane foulant could be broadly categorized to four types mainly organics, inorganics, particulates and micro-organisms (Guo et al., 2012). Table 3.3 has indicated high concentrations of Fe (0.76 mg/L) and Mn (0.13 mg/L) in the feed water which suggested inorganic fouling in the UF system was highly possible. Comparisons of the CEB cleanings effectiveness in Figure 3.5, Figure 3.6 and Table 3.4 have also pointed out that inorganic membrane fouling occurred in the system.

This case study water treatment plant implements direct filtration of the aerated river water without dosing any chemical for the coagulation-flocculation process. Aeration on the river water promotes the oxidation of Fe and Mn ions to precipitate as hydroxides for solid-liquid separation in the UF process (Choo et al., 2005). In a typical water treatment plant, the coagulation-flocculation of the river water precedes a clarification process. Clarification is an important process in water treatment to allow heavy formed

solids particles through coagulation-flocculation process to settle down and reduce the solids loading prior to the filtration system (Burke et al., 2011). Unless the solids loading of the feed water is low (such as 20 NTU or below), feed water with high solids loading is normally recommended to undergo a clarification process prior to UF.

Figure 3.4 and Table 3.3 have shown that the feed water turbidity could sometimes increase up to 68 NTU which contained high concentrations of Fe and Mn as well. Without coagulation-flocculation and clarification processes, all these metal hydroxides would attached on the membrane surface together as the cake filtration layer. The solubility product of metal hydroxides ( $K_{sp}$ ) mainly Fe(OH)<sub>3</sub> and Mn(OH)<sub>3</sub> as well as the ionic product of the feed water was calculated and shown in Table 3.5. The ionic product of both the metal hydroxides have higher values than their respective  $K_{sp}$  suggesting that precipitation of Fe(OH)<sub>3</sub> and Mn(OH)<sub>3</sub> were very likely to occur on the UF membrane surface.

Fe in feed water (mg/L)	[Fe <sup>3+</sup> ] (mol/L)	Feed water pH	[OH <sup>-</sup> ] (mol/L)	<i>K</i> <sub>sp</sub> of Fe(OH) <sub>3</sub>	Ionic product of [Fe <sup>3+</sup> ][OH <sup>-</sup> ] <sup>3</sup>
0.76	1.36 X10 <sup>-5</sup>	6.8	6.31 X 10 <sup>-8</sup>	6.30 X 10 <sup>-38</sup>	3.42 X 10 <sup>-27</sup>
	2		[0]]-]		
Mn in feed water (mg/L)	[Mn <sup>3+</sup> ] (mol/L)	Feed water pH	[OH] (mol/L)	K <sub>sp</sub> of Mn(OH) <sub>3</sub>	Ionic product of [Mn <sup>3+</sup> ][OH <sup>-</sup> ] <sup>3</sup>

 Table 3.5: Ionic product and K<sub>sp</sub> of feed water

The pH of 6.8 in the feed water indicates the possibilities of metal hydroxides precipitation on the membrane surface (Pearce, 2007a). Precipitation of the metal hydroxides would form a thin cake filtration layer on the membrane surface and

eventually causes inorganic fouling. Researchers have reported that metal hydroxides were common inorganic foulant (Shirazi et al., 2010). The high removal efficiency of more than 98% for both the Fe and Mn in the filtrate indicated that high concentrations of metal hydroxides were attached on the membrane surface which might not be removed completely during hydraulic backwash and CEB.

# 3.4.6 Electricity consumption

Operational cost is one of the most important commercial aspects of an industrialscale UF membrane water treatment plant. Due to the fact that this water treatment plant operates under direct filtration method, no prior chemical was dosed into the system for the coagulation-flocculation process. The main operational cost would be the electricity consumption for the treatment processes. Membrane fouling would incur reduction of permeability and increased the TMP in order to maintain constant flux filtration. The pump affinity law shown in equation (3.1) indicates that the increase of electricity power required ( $W_1$  and  $W_2$ ) to reach higher pressure is an exponential correlation to the pressure in the system ( $H_1$  and  $H_2$ ) (Wang et al., 2012).

$$\frac{W_1}{W_2} = \left(\frac{H_1}{H_2}\right)^{1.5} \tag{3.1}$$

This implies that even a slight 0.1 Bar increase in feed water pressure would have a significant exponential impact on the electricity consumption. As mentioned earlier, the fouling of the membrane increases the filtration resistance which raises the feed water

pressure and TMP. In order to maintain constant flux filtration, higher operation pressure was necessary to overcome the filtration resistance. Figure 3.7 shows the feed water pressure and electricity consumption increased from March until December 2013 at the UF membrane water treatment plant.



Figure 3.7: Electricity and feed water pressure increase in 2013

The calculated electricity in Figure 3.7 using equation (3.1) indicated close agreement with slightly lower values compared with the actual electricity consumption. Literature has reported an estimated electricity consumption of 0.20 kWh/m<sup>3</sup> was expected for the production of potable water in large-scale using UF membrane systems (Pearce, 2008). During the initial first few months (March until July 2013) of the water treatment plant operations, the actual electricity consumption was lower than 0.20 kWh/m<sup>3</sup>. The increase of the feed water pressure causes the electricity consumption to surge up in accordance to equation (3.1). A difference of 0.8 Bar or 35% increased of feed water pressure from March until December 2013 had caused a 60% surge on the

electricity consumption. This gradual increase was caused by membrane fouling which reduces the permeability resulting in higher feed water pressure to generate similar filtration flux rate. It is relatively common to observe some degree of membrane fouling conditions after 3 to 6 months of continuous operation on a typical UF membrane water treatment plant which requires further attention and corrective actions.

One of the more rigorous cleaning methods beside CEB is called clean in place (CIP) procedures. In the CIP process, instead of soaking the membrane in strong chemicals, these chemical are circulated in the hollow fibre membrane capillaries for up to 12 hours continuously. The amount of membrane downtime and chemical consumption are high for CIP process and these cleaning procedures are normally recommended once between 6 to 12 months of continuous operation and not on a monthly basis. Membrane fouling is unavoidable in most conditions and these rigorous chemicals cleaning procedures are necessary to recover back the permeability of the membranes.

#### **3.5** Findings of the case study

The main objective of this case study was to analyze the major issues encountered at an industrial-scale UF membrane water treatment plant with reference to literature reports. Through this case study, it could be noticed that most of the problems encountered in this UF membrane water treatment plant have been reported through literature. Critical comments on these findings were summarized in Table 3.6. Such findings suggested that literature information could provide valuable insight to mitigate some of the problems faced in an industrial-scale UF system. Bridging the gaps between industrial practices and information from literature would have immense benefits to improve the overall operation of the UF system. A more efficient UF system operation would yield much lower operational cost and less wastage of resources.

No.	Design and operational issues	Findings from case study	Literature information	Critical comments
1.	Membrane surface area	Grab samples of feed water was conducted and simulation software provided by the membrane manufacturer was used as the basis to determine the total membrane surface area required.	Extensive pilot-scale studies of at least 4 months were encouraged to be conducted to ascertain the required membrane surface area. (Holloway et al., 2015; Loganathan et al., 2016; Urgun-Demirtas et al., 2013)	Complexity of the interaction between feed water and membrane characteristics required comprehensive studies to determine membrane surface area and filtration flux.
2. Feed/raw The fee water river w characteristics NTU o based o		The feed/raw water from the river was assumed to be 20 NTU or below all the time based on samples collected.	River water characteristics and turbidity is highly dynamic and could have substantial changes during heavy rainfalls with variation in humic acid, inorganic salts, biopolymer and heavy metals concentrations which could cause membrane fouling. (Choo et al., 2005; Lee et al., 2016a; Shirazi et al., 2010; Sioutopoulos & Karabelas, 2012; Tian et al., 2013a)	Fluctuation of the river water during heavy rainfalls pose serious problem to the UF system as higher turbidity implies higher solids loading which causes higher possibilities of membrane fouling.
3.	Chemicals for UF membrane cleaning	The chemicals (HCl and NaOH) for membrane cleaning were predetermined by membrane manufacturer recommendation during design stage.	Although HCl (Ujihara et al., 2016) and NaOH (Antón et al., 2015) are commonly used for PES membrane cleaning, there are other more effective chemical such as NaOCl (Li et al., 2016b) which should be considered as well.	Operators of the UF system should be informed that the cleaning chemical might require to be examined from time to time depending on its effectiveness to remove the foulant.
4.	Hydraulic backwash and chemicals cleaning efficiency	Hydraulic backwash only marginally reduces the feed water pressure while the alkaline and acid CEB were more effective.	Effectiveness of chemical cleanings are dependence of the foulant types because certain chemicals are foulant specific (Alzahrani et al., 2013).	Constant observation of the chemical cleaning effectiveness is important. Feed water characteristics changes might cause certain foulant to accumulate on the membrane surface.
5.	UF membrane fouling	Membrane fouling was suspected to be caused by precipitation of inorganic metal hydroxides which were more effective with acid CEB cleanings.	Metal hydroxides are common foulant on membrane surface for natural feed water (Pearce, 2007a; Shirazi et al., 2010)	Prior coagulation- flocculation and clarification processes are recommended for natural feed water with high turbidity to mitigate membrane fouling.
6.	Electricity consumption	Initially the electricity consumption of the water treatment plant was less than 0.20 kWh/m <sup>3</sup> but gradually increases due to membrane fouling.	Recommendation from literature indicates electricity consumption should be around 0.20 kWh/m <sup>3</sup> (Pearce, 2008).	Preventive actions such as more rigorous chemical cleaning should be conducted when electricity consumption increases significantly due to membrane fouling.

# Table 3.6: Summary analysis in the case study

# 3.6 Summary

Through this case study, a comprehensive analyses of the difficulties encountered in an industrial-scale UF membrane water treatment plant have been discussed. Issues such as determining total membrane surface area, fluctuation of feed water characteristics, selection of chemicals for membrane cleaning, UF membrane fouling, electricity consumption, efficiency of hydraulic backwash and chemical cleanings have been elaborated in details. All these analyses were compared to information obtained from literature to determine the causes and possible solutions. Establishing this link between information from literature and industrial practices enhances the comprehension of the problems encountered and effective solutions could be proposed. Some possible suggestions to improve the operation of the system include increasing the quantity of the UF membrane modules and further research on using non-Aluminium based coagulant in the UF membrane water treatment system.

#### **CHAPTER 4:**

# EVALUATION AND COMPARISON OF ULTRAFILTRATION AND CONVENTIONAL WATER TREATMENT SYSTEMS

Water treatment plants/systems are essential facilities to produce clean and safe potable/drinking water to consumers through the public-piped water supply networks. The sustainable development of such facilities are manifested as part of an integrated approach to ensure environmentally friendly, waste minimization, economic and social prosperity (Khalili et al., 2015). In this chapter, detailed evaluation and comparison on both of the industrial-scale UF and conventional water treatment systems have been further elaborated with comprehensive data analysis.

#### 4.1 Introduction

Previously in Chapter 3, detailed analysis on the common technical issues related to the industrial-scale UF membrane water treatment plant was presented. The same UF membrane water treatment system discussed earlier in Chapter 3 was further analyzed in other aspects. In this chapter, a case study to evaluate and compare various aspects of this UF system against the conventional water treatment system has been conducted. Before this UF system was constructed, a conventional water treatment plant was already in operation 30 years ago at the same location. The UF system was merely the extension of this water treatment plant to further increase the capacity of the potable water supply from this treatment facility. Once the UF water treatment system commences operation, both the UF and conventional water treatment systems were made available at the same treatment plant and drawing similar river water source through the common main incoming pipeline. The fact that both the UF and conventional water treatment systems were treating the same feed water from the river provides a reliable and consistent case study for comparison. Evaluation and comparison on both treatment systems have been conducted in five aspects such as capital cost, operational cost, maintenance cost, analysis of filtrate quality and the overall water losses. All these five aspects encompassed the commercial feasibility and the treatment systems performance which have been further elaborated in the subsequent sections of this chapter.

# 4.2 Background

A typical conventional potable water treatment plant comprises a few common main processes such as coagulation-flocculation, clarification or sedimentation and final polishing with media/sand filtration (Pestana et al., 2016). The utilization of media filtration process is the most common physical particles removal polishing for industrial-scale water treatment plants (Zouboulis et al., 2007). Rapid development on membrane technology has motivated design engineers to replace all these conventional treatment processes with a single step of direct feed UF (Tian et al., 2013a).

In a conventional water treatment system, chemicals such as coagulant and flocculant are dosed in the raw water to promote the formation of larger flocs for the subsequent solid-liquid separation processes. The characteristics of the flocs played an important role to ensure the solid-liquid separation is effective (Zhao et al., 2014). There are many factors governing the formation of flocs such as pH, temperature, raw water characteristics, coagulant type and dosage (Mitrouli et al., 2008). Laboratory experiments have shown that filtration time through the media filter as well as the floc characteristics have significant impact on the filtrate water turbidity and quality. Conventional media filtration operates under depth filtration concept whereby the flocs are retained throughout the media bed (Noyes et al., 2015). This indicates that direct filtration through media filter without the formation of flocs are not possible to produce the desired filtrate quality.

Unlike the media filter, UF operates under the cake/surface filtration principle. Fine solids larger than the pore size of the UF membrane are trapped on the surface forming a porous cake filtration layer (Bugge et al., 2012). Direct feed filtration without flocs formation in the coagulation-flocculation process is possible with UF membrane to achieve effective solid-liquid separation. Figure 4.1 illustrate the concepts of depth filtration on conventional media filter and cake/surface filtration on UF membrane.



Figure 4.1: Illustration of conventional media filtration and UF

Figure 4.1 shows that depth filtration in the conventional system requires a significant filter media bed height to trapped the particles. Typical filter media bed height is between 1.0 – 1.5 meter. UF membranes are commonly packed into pressurized membrane modules to reduce the floor space requirement. Membrane filtration has definite advantage on the lesser floor space requirement compared to the conventional media filters (Vedavyasan, 2007). The filtration capability of the UF systems could be controlled by carefully selecting the membrane pore size and material allowing it to even segregate viruses and microorganism such as bacteria from the water (Arkhangelsky et al., 2012). One of the major drawbacks of UF systems is the membrane fouling issues which are being extensively researched (El-Abbassi et al., 2014; Filloux et al., 2012; Shirazi et al., 2010; Wang et al., 2014; Xiarchos et al., 2003). It is also deemed as a relatively "expensive" technology compared to the conventional system applied in water treatment (Massé et al., 2011).

In recent decades, the concept of sustainable development has been gaining massive attention (Khalili et al., 2015). Stakeholders and businesses are embracing this concept by re-aligning their production strategies towards sustainable development (Sen et al., 2015). Case studies conducted by researchers have demonstrated and highlighted such sustainability in waste management, commercial production and environmental protection (Alkaya & Demirer, 2014; Handley et al., 2002; Liu et al., 2014; Nunes et al., 2014). Commercial, quality outputs and environmental sustainability impacts are essential issues of any water treatment plants worth investigating for the long term benefits.

Case study on an industrial-scale membrane system at the Barcelona Metropolitan Area elucidated the contribution of reverse osmosis (RO) on the quality of drinking water (Raich-Montiu et al., 2014). The filtrate was examined extensively on organoleptic quality requirements of potable water. A similar case study was also conducted on an industrial-scale UF membrane water treatment plant at Nantong, China (Xiao et al., 2012). This case study has indicated high turbidity removal up to 99% with absence of coliform bacteria from the filtrate. Industrial-scale membrane systems have been proven through such case studies to be capable of producing consistent high quality of outputs. Both of these case studies have particularly examined the filtrate water quality without further detailed analysis on the environmental impact and commercial aspects of the water treatment systems. The subsequent sections of this chapter further elaborate on various commercial, quality and environmental aspects of the industrial-scale UF and conventional water treatment systems.

# 4.3 Methodology

In this second evaluation or case study, an industrial-scale water treatment plant located at Kelantan, Malaysia was selected. This water treatment plant consists of both UF and conventional media filtration systems situated side by side. The industrial-scale UF membrane water treatment system investigated in this study is the same system mentioned earlier in Chapter 3. In this subsequent case study, the scope of evaluation has expanded to include the conventional media filtration water treatment system which was in operation much earlier and located next to the UF system. There are five aspects which have been detailed examined and analyzed in both of these systems. The aspects are capital cost, operational cost, maintenance cost, analysis of filtrate quality and the overall water losses. Environmental aspects such as the compositions of the sludge discharge from both treatment systems were also analyzed. Figure 4.2 shows the simplified flow diagram of all the processes involved in both the water treatment systems.



Figure 4.2: Process flow block diagram of water treatment systems

The water treatment plant depicted in Figure 4.2 shows that both the conventional and UF systems were drawing the same river water source and subjected to natural aeration through a cascading aerator before branching to the two different systems. Both systems have been designed to accommodate different treatment capacity whereby the conventional system could produce up to 11 million liters a day (MLD) while the UF system could produce 14 MLD of treated water. The treated water was then supplied to multiple areas or township through two separate supply pipelines.
This water treatment plant was constructed more than 30 years ago with only the conventional treatment system and has been supplying potable water to the nearby township ever since. An upgrading works in 2011 encompassed the construction of a larger cascading aerator in the process line as well as a new UF system. After passing through the cascading aerator, the raw water to the conventional system was dosed with Aluminium (Al) based coagulant. The dosed feed water was then channeled to a series of wooden baffle plates in the flocculation chamber for the coagulation-flocculation process. This process allows agglomeration of the suspended solids into bigger and denser flocs for the subsequent sedimentation or solid-liquid clarification process. There are two units of sedimentation clarifiers arranged in parallel for this process. Each clarifier was designed with surface loading rate of 2.81 m/hr which were in accordance to the recommended range of between 0.71 - 3.30 m/hr reported in literature (Kawamura, 2000). Subsequently the clarified water was channeled to four units of gravity media/sand filters. These filters consist of fine sand with effective size between 0.7 - 1.4 mm diameter acts as the media bed for the depth filtration. The filtration rate for each filters were 7.0 m/hr which was well below the reported 10.0 m/hr filtration rate for gravity filter in most industrial-scale water treatment plants (Zouboulis et al., 2007). Finally before the filtrate was pumped out and distributed through the pipeline, chlorine gas was dosed to ensure between 1.5 - 2.0 mg/L of free chlorine residual was detected in the final treated water. Figure 4.3 shows the detailed process of the conventional water treatment system.



Figure 4.3: Schematic block diagram of the conventional water treatment system

Construction of the new UF membrane water treatment system was completed in 2013 and located next to the conventional treatment system. The pre-treatment of the UF system comprises of an extended aerator and pressurized sand filters. In the extended aerator, forced aeration using air blower and diffusers were conducted. After passing through the extended aerator, the feed water was pumped into 4 units of pressurized sand filters to remove large particulate matters. The filtration rate of these pressurized sand filters were set at 15 m/hr which were much higher than gravity filters systems. After these pressurized filters, the pre-treated water was pumped into 120 units of UF membrane modules installed in parallel. The UF hollow fibre membrane modules were made from modified Polyethersulfone (mPES) manufactured by Inge GmbH, Germany. Finally the filtrate was disinfected with Sodium Hypochlorite (NaOCI) before supplying to the public-piped supply networks. Figure 4.4 shows the detailed block diagram of the UF system.



Figure 4.4: Schematic block diagram of the UF system

The same river water was channeled to both of the conventional and UF water treatment systems in this water treatment plant. Studies conducted by researchers have shown that natural organic matter (NOM) in natural water sources was a major issue in the treatment processes (Joseph et al., 2012). In the conventional water treatment system, different types and amount of NOM would affect the coagulant dosage to produce optimum flocs size in the coagulation-flocculation process. NOM has a significant negative impact on the UF membrane fouling propensity. Using the same river water source into both systems would allow a more comprehensive and fair comparison of the systems.

### 4.4 **Results and discussions**

The results of this case study on the conventional and UF systems were analyzed and discussed in this section. All the relevant operational data and laboratory analysis from both treatment systems were collected from the period between the year 2013 and 2014

for evaluations. These data were arranged in five aspects which are further elaborated and critically discussed in the following sections.

## 4.4.1 Capital cost of treatment systems

One of the most essential aspects of evaluating the feasibility of a water treatment system is the capital cost or expenditure. Capital expenditure (CAPEX) is broadly defined as the cost to procure fixed assets which encompass the land, mechanical equipment, electrical control system, civil structures and other ancillary hardware to complete all the treatment processes. Since both of the UF and conventional water treatment systems were constructed on a gap of a few decades, construction cost estimation is required to be adjusted for a fair evaluation on current market value. A rationalized updated cost of construction was established in order for a comprehensive comparison between the two systems. The conventional system was built more than 30 years ago and it would definitely cost much more in 2013 due to inflation rate. Yearly inflation data of Malaysia's domestic market published by "The World Bank, 2014) was used to extrapolate and estimate the construction cost for this conventional system in 2013 which correspond to the completion year of the UF system. In Figure 4.5, the yearly inflation rate was added into the initial construction cost of the conventional system back from 1980 until 2013.



Figure 4.5: Construction cost in 2013 estimated based on annual inflation rate

The estimated cost of construction for the conventional system depicted in Figure 4.5 indicated a much reasonable cost of construction in 2013. As mentioned earlier, the treatment capacity for the conventional system was 11 MLD while the UF system was designed for 14 MLD. In order to rationalize both treatment capacities, the cost of construction per m<sup>3</sup> of treated water was taken into consideration. Another important cost factor besides the construction cost would be the cost for the land to accommodate the treatment systems. Due to scarcity of available land especially in urban area, this poses a significant cost to the owner of the treatment systems. Table 4.1 shows all the relevant data of the capital expenditure and land area required by the two systems.

	UF system	Conventional media filtration	
Cost of construction in 2013	USD 3, 710, 000 (actual)	USD 2, 760, 726 (estimated)	
Treatment volume/capacity	14, 000 $m^3/d$	11, 000 $m^3/d$	
Land requirement	528 m <sup>2</sup>	1, 376 m <sup>2</sup>	
Cost/m <sup>3</sup> capacity	USD 265	USD 251	
Land/m <sup>3</sup> capacity	$0.038 \text{ m}^2$	$0.125 \text{ m}^2$	

Table 4.1: Capital expenditure and land area required

The details presented in Table 4.1 provided a rationalized construction cost and land requirement for both systems. It was estimated that an 11 MLD conventional media filtration system would have cost USD 2, 760, 726 to construct while the actual cost of a 14 MLD UF system was USD 3, 710, 000 in the year 2013. The UF system construction cost would be USD 265/m<sup>3</sup> of treated water capacity compared with USD 251/m<sup>3</sup> for the conventional system. Literature has reported that generally the construction cost of membrane water treatment systems would be significantly higher than the conventional system (Pearce, 2007b). The advantage of the membrane systems are exhibited through the smaller land required compared to the conventional water treatment system. Based on data in Table 4.1 the construction cost for the UF system was only 5.6% higher but it requires 69.6% less land space for the construction compared to the conventional system. As the demand for membrane systems continue to increase on a global scale, more cost efficient membrane manufacturing methods are being developed due to economies of scale. The continual decline of UF membrane cost and the lesser space requirement has made this system very attractive for large-scale production (Tian et al., 2013b). Acquiring land for the construction of water treatment plants especially in the urban area would become a more costly effort in future. Land in urban area is typically

more expensive than rural area due to their accessibilities to multiple facilities (Liu et al., 2015).

Various aspects contributed to the capital expenditure on both treatment systems. Literature has reported that sensitivity analysis can be applied to identify the key factors which have significant impacts on certain aspects (Igos et al., 2014). In order to further illustrate the effect of the land price towards both the systems capital expenditure, a sensitivity analysis was conducted and shown in Figure 4.6. The capital expenditure which encompassed the construction cost and the estimated land procurement cost was calculated. Assumptions were made that the land values were between 10 - 300 USD/m<sup>2</sup> as indicated in Figure 4.6.



Figure 4.6: Capital expenditure estimated based on various land values

The sensitivity analysis shown on Figure 4.6 indicated that once the land value reached or exceeded  $170 \text{ USD/m}^2$ , the UF system capital expenditure (for both 14 MLD

and 11 MLD) became much lower compared to the conventional water treatment system. Higher land savings has made the UF system becomes an attractive and feasible option in land scarce urban area.

### 4.4.2 **Operational cost of treatment systems**

Besides the capital expenditure of the treatment systems, the long term operational cost or operation expenditure (OPEX) is an equally important factor to stakeholders. Operational cost is defined as related expenses to operate the treatment systems in order to produce the required quantity and quality of potable/drinking water from the facilities. The most significant operational cost for water treatment systems are electricity and chemical expenditures. Electricity is utilized to drive the motors for pumps and other mechanical equipment while chemicals are required for the coagulation-flocculation process, cleaning of the UF membrane and disinfection for the treated water.

As mentioned earlier, the coagulation-flocculation process is essential for the conventional media filtration system. Literature has reported that dense flocs from the coagulation-flocculation process allows high removal efficiency of the fine solids by attaching them to the media grain (Zahrim & Hilal, 2013). The conventional water treatment system in this case study was utilizing Aluminium Chlorohydrate (ACH) as the chemical for coagulation-flocculation. According to literature reports, ACH is a much more effective chemical than Aluminium Sulfate (alum). It requires 60% - 70% less dosage than alum to remove organic in water treatment (Wang et al., 2008). ACH has lower alkalinity consumption and the coagulated suspension pH only decreases by less than 0.5. Another type of chemical used in the conventional system in this case study was the chlorine gas (Cl<sub>2</sub>) for final disinfection. Chlorine is an effective

disinfectant to counteract microbial presence in drinking water supply (Monteiro et al., 2014). The conventional water treatment system maintains the chlorine residual of the treated water to between 1.5 - 2.0 mg/L with periodical control and monitoring.

The usage of chemical for the UF system in this case study was very minimal as it was a direct filtration process which does not necessitate any coagulation-flocculation prior to filtration. Literature has suggested that the coagulation process have minimal effect on eliminating organic matters which would cause membrane fouling (Xiao et al., 2012). Most of the large solids particles from the feed water have been separated by the pressurized sand filters after the aeration process. The UF membrane will further remove the fine solids, bacteria and viruses which were larger than 0.02 µm to produce crystal clear filtrate. The final disinfection was conducted by dosing Sodium Hypochlorite (NaOCI) to the filtrate before supplying as treated water. Besides NaOCI the other chemicals used for the UF system were Sodium Hydroxide (NaOH) and Hydrochloric Acid (HCI) for membrane cleaning. Both NaOH and HCI have gained acceptance as UF membrane cleaning chemicals because of its economic feasibility (Kumar & Pal, 2013; Regula et al., 2014). The UF membrane manufacturer of this case study has also expressed their approval and recommendation of both chemicals for the membrane cleaning through CEB.

Another main component of the operational cost of a water treatment system is the electricity utilization. Electricity is required to drive the pumps, blowers, compressors and other mechanical equipment in the treatment processes. Under acceptable raw/feed water quality conditions, the UF system would incurred much higher cost compared to the conventional treatment system (Bonnelye et al., 2008). The electricity utilization was much higher for the UF system in this case study as it was a pressure driven process unlike the conventional gravity media/sand filtration. Table 4.2 and Table 4.3 indicate the chemical and electricity consumption for both the UF and conventional water

treatment systems. Since this case study water treatment plant is located in Malaysia, all relevant expenditures were in accordance to local rate. These chemical and electricity costs were estimated based on Malaysia's current market values in 2014 and might differs in other countries or regions of the world.

	UF system		<b>Conventional media filtration</b>			
	Usage purpose	Cost for 1,000 m <sup>3</sup> treated water	Average dosage	Cost for 1,000 m <sup>3</sup> treated water		
Coagulant (ACH)	-	-	11.0 mg/L	USD 9.57		
Sodium hydroxide (48%)	Membrane cleaning	AembraneUSD 2.66cleaning		-		
Hydrochloric acid (33%)	Membrane cleaning	USD 1.46		-		
Cost of chemical for each 1,000 m <sup>3</sup> of treated water produced		USD 4.12		USD 9.57		

 Table 4.2: Chemical consumption and estimated cost of water treatment

	UF system (power consumption)	<b>Conventional media</b> <b>filtration</b> (power consumption)	
Air blower	32.0 kWh	0.1 kWh	
Chlorine booster pump	-	4.0 kWh	
Backwash pump	2.5 kWh	0.2 kWh	
Pressurized filter feed pump	30.0 kWh	-	
UF feed pump	55.0 kWh	-	
Air compressor	0.2 kWh	-	
NaOCl/ACH dosing pump	0.3 kWh	0.2 kWh	
Total electricity consumed in 1 hour	120.0 kWh (for 576 m <sup>3</sup> of water)	4.5 kWh (for 458 m <sup>3</sup> of water)	
Total electricity consumed per $1,000 \text{ m}^3$ of treated water produced	208.3 kWh	9.8 kWh	
Cost of electricity per 1,000 m <sup>3</sup> of treated water produced	USD 31.25	USD 1.47	

The unit price of ACH was estimated at 0.87 USD/kg in Table 4.2 while electricity was priced at 0.15 USD/kWh in Table 4.3. Data shown in Table 4.2 and Table 4.3 indicated that the estimated operational expenditure for the UF system (inclusive of chemical and electricity) was much higher at USD 35.37 compared to the conventional system at USD 11.04 to produce 1, 000 m<sup>3</sup> of treated water. The estimated operational expenditure for the UF system was more than 3 times higher than the conventional system mainly because of the higher electricity utilization due to the pressure driven membrane filtration process. Nevertheless, one of the distinctive advantages of UF system is the cake/surface filtration mechanism which does not require prior coagulation-flocculation process unlike the conventional system. This enable a huge reduction in the chemical cost which was only 43% compared to the conventional system. Chemicals (HCl and NaOH) were used for membrane cleaning in the UF system while ACH was used as coagulant for the agglomeration of flocs in the conventional system.

Similar sensitivity analyses presented on the capital expenditure earlier were also conducted on the operational expenditure. Evaluation was carried out on the various breakdown of the operational expenditure for both systems in Figure 4.7. This figure illustrated four possible scenarios in graph form to further correlate various possibilities of the fluctuations on the operational expenditure as follows:-

Category A – Electricity cost was reduced by 50% and chemical cost remains

- Category B Chemical cost was increased by 100% and electricity price remains
- Category C Electricity cost was reduced by 50% and chemical cost increased by 100%
- Category D Chemical and electricity cost remains the same as indicated in Table 4.2 and Table 4.3.



Figure 4.7: Four categories of sensitivity analysis on operational expenditure

The information shown in Figure 4.7 indicated that all the four scenarios (Category A, B, C and D) have a common conclusion that the conventional media filtration operational cost was always lower than the UF system. It is worth taking note that Category C has indicated a much smaller margin of operational cost between these two systems. This scenario shows that when the cost of electricity has gone down significantly while the cost of chemical continues to escalate due to inflation, there are high possibilities that the operational costs of both systems might be only marginally different. One of the possibilities of descending electricity cost is through the use of renewable energy resources such as solar or wind generation of electricity. The obstacles of utilizing such renewable energy sources are the huge amount of initial capital expenditure to construct the required facilities. In a much wider aspect, renewable energy sources are deemed to be much more environmentally friendly and should be considered as the "fuel" for the future. Throughout the years, global inflation

of commodities has also increased the price of water treatment chemicals on a yearly basis. There are very little doubts that the price of chemicals would keep on increasing in years to come. These two main drivers (low cost renewable energy and high cost of chemicals) would enable the operational cost of the UF system to level off with the conventional systems in the near future.

## 4.4.3 Maintenance cost of treatment systems

Water treatment facilities and equipment are prone to wear and tear which requires periodic maintenance. Maintenance costs are expenses required to ensure the treatment system components in relatively optimum condition for continuous operation. As mentioned earlier, the UF system is a pressure driven process which requires a lot of mechanical rotating equipment unlike the conventional system which is a gravity driven process. The high pressure built-up in the piping systems causes frequent leakages to occur and higher maintenance works were required. Table 4.4 shows the comparison of estimated maintenance cost for the UF system as well as the conventional system. The estimated maintenance cost for both the treatment systems were conducted based on records obtained from 2013 until 2014 for a 12 months period. Estimated total yearly maintenance cost for the UF system was much higher than the conventional system which were also in accordance to the literature report conducted by other researchers (Bonnelye et al., 2008). In this case study, the UF system was a fully automated system while the conventional system was a fully manual operated system. The operators in the water treatment plant were responsible for the operation of both systems in each working shifts. These operators spent much longer time attending to the conventional system as all the filter backwash, coagulant dosage and final disinfection were carried out by the operators manually.

	UF system	Conventional media filtration
Automation components maintenance and piping system leakages repair	3, 500 USD/year	500 USD/year
UF membrane chemical cleaning (Clean in place or CIP)	1, 500 USD/year	-
Cleaning of sludge in clarifiers and filter tanks	-	1, 000 USD/year
Rotating equipment greasing, lubrication and spare parts replacements	200 USD/year	100 USD/year
Total cost of maintenance in a year	5, 200 USD/year	1, 600 USD/year

Table 4.4: Estimated maintenance cost for the UF and conventional systems

Information in Table 4.4 has clearly indicated that up to 67% of the estimated yearly maintenance cost for the UF system was spent on the automation components and pipes leakages. Only 31% of the yearly estimated maintenance cost was used for the same purpose (repairing pipes leakages) on the conventional system. The constant switching between filtration and backwash sequences every hour for the UF system necessitates full automation operation. Such automation might not be necessary for the conventional media filtration system as the backwash was only initiated after 48 hours of filtration sequence. The backwash sequence for all the media filters were executed by the operators manually in this case study.

## 4.4.4 Analysis of filtrate quality

The quality of the filtrate produced by both systems was analyzed in detailed under this case study as well. Literature has reported experimental studies conducted by researchers using seawater as the feed water to both conventional and UF systems (Guastalli et al., 2013). This pilot-scale study has shown that the UF system produced much higher stability and excellent quality of the filtrate compared to the conventional system. Similar results were also observed in the evaluation of industrial-scale water treatment systems under this case study. Figure 4.8 shows the analysis results of the feed water and the filtrate turbidity from both conventional and UF systems in May 2013. Under normal conditions, the feed water turbidity from the river should be 20 NTU or less which was the designed basis for the UF system. Unfortunately during certain rainy days, the turbidity increased to more than 20 NTU reaching almost 60 NTU occasionally. Such feed water characteristic/turbidity fluctuation requires the operators to re-adjust the coagulant dosage to ensure optimum flocs size was formed in the coagulation-flocculation process for the conventional system.



Figure 4.8: Feed water and filtrate turbidity in May 2013

In Figure 4.8, the UF filtrate turbidity was consistently below 1 NTU irrespective of the feed water turbidity fluctuation. As for the conventional media filtration system, the filtrate turbidity fluctuates in a similar pattern as the feed water turbidity. The main reason behind the fluctuation of filtrate turbidity was because the conventional system would require re-adjustment of the coagulant dosage when there were characteristic changes such as turbidity fluctuation in the feed water. Operators of the treatment plant would need to consistently monitor the feed water characteristic and at the same time re-adjust the coagulant dosage to ensure optimum flocs formation (Wu & Lo, 2010). Any deficiency in the coagulation-flocculation process would cause the depth filtration mechanism in the media filter to have lower efficiency of solid-liquid separation and produce lower quality of filtrate which exhibited higher turbidity.

The average filtrate turbidity for the UF system indicated in Figure 4.8 was 0.37 NTU while the average filtrate turbidity of the conventional system was 1.47 NTU. By examining these data, it could be concluded that the UF system consistently produced much higher quality of filtrate in terms of lower turbidity compared to the conventional system. As mentioned earlier, the cake/surface filtration mechanism of the UF membrane allows direct feed of the feed water without jeopardizing on the solid-liquid separation process.

Besides the filtrate turbidity, a few important aspects concerning the quality of the filtrate are in terms of dissolved organic carbon (DOC) and chemical oxygen demand (COD) concentrations. A detailed analysis of the feed water and filtrate from both systems were conducted to determine the removal efficiency as well as the pH. Table 4.5 shows the water samples analysis of the feed water and the filtrate from both systems.

	Feed water	UF system	Conventional media filtration
		(% removal)	(% removal)
DOC (mg/L)	3.6	0.7 (81%)	2.1 (42%)
COD (mg/L)	8.0	5.0 (38%)	2.0 (75%)
рН	7.1	6.9	6.7

Table 4.5: Removal efficiency of DOC and COD

Literature has reported that the DOC removal of membrane processes were much better than conventional media filtration (Kabsch-Korbutowicz, 2006). The data shown in Table 4.5 indicates similar observation with 81% removal efficiency of DOC from the feed water compared with only 42% in the conventional system. The presence of DOC in surface water was known to be a precursor of the formation of disinfection byproducts which cause a lot of health related issues (Cool et al., 2014). Analyses of the feed water was found to consists of 3.6 mg/L of DOC which was relatively low compared to the reported mean average of 7.24 mg/L (Cool et al., 2014). DOC is not a frequently monitored parameter in drinking water for Malaysia but nevertheless it is a good practice to consistently ensure the DOC content is low in the chlorinated potable water to reduce the amount of hazardous disinfectant by-products. Experimental studies using pilot plant by other researchers have indicated that the removal rate of DOC was much higher in UF systems compared to the conventional media filtration system (Guastalli et al., 2013). This case study on UF and conventional industrial-scale water treatment systems also show similar results as indicated in Table 4.5. The UF system DOC removal efficiency (81%) was almost double of the conventional media filtration system (42%).

Besides DOC, other undesired contaminant in drinking water supply is the high COD content. It was reported that COD was not a major issue in water treatment plants at Malaysia (Hasan et al., 2011). The high concentration of COD is undesirable mainly

because it leads to the exhaustion of dissolved oxygen and promotes the occurrence of septic or lack of oxygen condition. Analysis of the feed water samples only indicated 8 mg/L of COD which complies with the recommendation of less than 10 mg/L in drinking water by Ministry of Health Malaysia as well as allowable limit reported in literature (Sarkar et al., 2007). It was speculated that the coagulation-flocculation process might be able to reduce some of the COD in surface water. This has been shown in the results from Table 4.5 whereby there was a 75% reduction in COD for the conventional water treatment system filtrate compared with only 38% for the direct feed UF system filtrate without any prior coagulation-flocculation.

There was also a noticeable drop of pH in the filtrate of the conventional system mainly due to the dosing of ACH for the coagulation-flocculation process. Equation (4.1) shows the hydrolysis reaction of ACH which lowered down the feed water pH by producing  $H^+$ . Since there was no chemical used prior to the filtration process for UF system, the filtrate would have very minimal pH difference than the feed water as shown in Table 4.5.

$$Al_2(OH)_5Cl \rightarrow Al_2(OH)_5^+ + Cl^- + H_2O \rightarrow 2Al(OH)_3 + H^+ + Cl^-$$

$$\tag{4.1}$$

The water samples analyses on both industrial-scale water treatment systems have shown the consistency of the UF system to produce low turbidity of filtrate without the use of any coagulant. Both the DOC and COD concentrations of the UF filtrate were also within acceptable levels.

## 4.4.5 **Overall water losses**

Water losses are critical issues at certain locations whereby the natural water resources have very limited feed water flow to the treatment plants. The main water losses from treatment plants are due to filter/membrane cleaning and sludge discharge. Table 4.6 shows the breakdown and overall water losses from both the water treatment systems.

	Ultrafiltration system	Conventional media filtration		
Feed water into system (average)	7, 420 m <sup>3</sup> /day	11, 152 m <sup>3</sup> /day		
Filtrate produced (average)	6, 600 $m^{3}/day$	10, 413 $m^3/day$		
Water losses through clarifiers (sludge discharge)		4.0%		
Water losses through media filter/membrane backwash	11.1%	2.6%		
Overall water losses	11.1%	6.6%		
Estimated dry sludge generation (80% dryness)	164 ton/month	148 ton/month		
Aluminium residual in sludge	Not detected	58 mg/L		

 Table 4.6: Breakdown and overall water losses

The analysis in Table 4.6 was conducted on May 2013 which was the same corresponding period as the filtrate and feed water data taken in Figure 4.8. Data in Table 4.6 shows that the UF system had higher water losses of 11.1% compared to the conventional system water losses of only 6.6%. Literature has reported water losses as high as 13.3% was recorded in UF system to mitigate the membrane fouling by allowing more frequent sludge discharge or backwash (Bai et al., 2013). The high

frequency of discharges in UF system might be necessary due to the fluctuating feed water turbidity indicated in Figure 4.8.

Conventional water treatment system has shown overall water losses of less than 7% which is in compliance to the recommendation by local authority in Malaysia. The major water losses of 4% were accumulated through the clarifiers whereby high concentrations of suspended solids were presence. These solids suspension or sludge consists of high concentrations of Aluminium residual were originated from the ACH dosed for the coagulation-flocculation process. Generally it was reported that the Aluminium sludge in a conventional potable water treatment plant was between 1% - 5% depending on the characteristic of the feed water (Tantawy, 2015). There were also an expected 2% - 3% water losses for the media filter backwash cleaning process (Kawamura, 2000).

Another issue worth taking note besides the total water losses of each system was the composition of the discharged sludge. As mentioned earlier, there was no chemical or coagulant dosed prior to the UF process. The sludge composition for the UF system should remain the same as the feed water but with much higher solids concentration. Since Aluminium based coagulant (ACH) was dosed for the coagulation-flocculation process prior to clarification and filtration, it should be expected that the sludge contains high concentrations of Aluminum residual. Table 4.6 have indicated that no Aluminium residual was detected in the sludge from the UF system while as high as 58 mg/L of Aluminium residual was detected in the sludge from the conventional system. A minor trace of Aluminium residual was always detected in the filtrate of the conventional system because of the dosing of ACH. There are reports that Aluminium residual in water was linked to possible development of Alzheimer's diseases, mental disorder or retardation in children and diseases caused by heavy metals accumulation (Tantawy, 2015). Besides not having any additional traces of Aluminium residual in the filtrate,

the UF system also does not produce sludge contaminated with Aluminium. The sludge was merely a more concentrated natural solids suspension from the river and could be readily discharge back to the downstream of the river with minimal environmental impact.

Restrictions imposed in some countries require Aluminium contaminated sludge from water treatment plants to undergo further treatment processes before disposal. It has been estimated that Aluminium sludge treatment and disposal can incurred cost of up to 130 USD/ton (Dassanayake et al., 2015). Data from Table 4.6 indicated that 148 tons of Aluminium contaminated sludge was generated every month in the conventional system. It could increase another additional 0.06 USD/m<sup>3</sup> for the overall operational cost of the conventional system treated water production. Not only that the Aluminium sludge required more effort and facilities for the disposal and environmental issues, it has also incurred additional cost to the overall production. A sustainable water treatment system should embrace long terms economical profit with minimal environmental impact.

### 4.5 Findings of the evaluation and comparison

There were five aspects which have been evaluated for both UF and conventional water treatment systems in this case study. Three of these aspects (capital cost, operational cost and maintenance cost) were related to the commercial feasibility of the systems while the remaining two aspects (filtrate quality and water losses) highlighted the quality and environmental concerns. These five aspects were selected based on its common acceptance in infrastructure and construction projects to elucidate its viability in environmental and commercial studies (Britton et al., 2013; Cheng, 2014; Dahal et al., 2015; Molinos-Senante et al., 2013; Zaman & Lee, 2015).

All the evaluation and cost analysis stated in this case study were based on local Malaysia conditions. It is suggested that the same trend would be observed in other parts of the world but with different prices due to currency exchange and inflation rates as all these commodities/chemicals/energy generation require intensive production techniques and rely on global market for the raw materials (Mercure & Salas, 2013). The sensitivity analyses indicated in Figure 4.6 and Figure 4.7 have shown that under certain conditions (eg. decrease in electricity price, increase in chemical cost, higher cost for land acquisition) the UF system would be very similarly feasible compared to the conventional system.

As mentioned earlier, sustainable development implies embracing both commercial and environmental impacts while ensuring quality of the final product. The UF system has shown promising results in producing consistently good quality of filtrate without using any coagulant. Although the total water losses of the UF system were much higher than the conventional system, it was observed that the sludge discharged was much more environmentally friendly. There was no Aluminium residual contamination detected in the sludge and it was safe to discharge it at the downstream of the river without further treatment. These sludge contains the same solids composition as the feed water with much higher solids concentration. The electricity utilization of this UF system was 0.21 kWh/m<sup>3</sup> of filtrate which was very close to the reported value of 0.20 kWh/m<sup>3</sup> in literature (Pearce, 2008). This UF system was generally automated with minimal operator's interception. The main drawbacks of the UF system were the overall higher cost (capital cost, operation cost and maintenance cost) and water losses compared to the conventional system.

This case study has indicated that the construction cost of the conventional system was much lower but requires a larger land area than the UF system. Data shown in Table 4.1 has indicated that construction cost (USD/m<sup>3</sup> of treated water) for the UF

system was 5.6% higher but requires only 30% land area ( $m^2/m^3$  of treated water) of the conventional system. These findings concurred with literature report which stated that UF system requires higher construction cost but utilize less land area than the conventional system (Pearce, 2007b). In this case study, it has been highlighted and also reported in literature that the UF system was a pressure driven process which entails high operational and maintenance cost (Bonnelye et al., 2008).

Due to the reliance of the coagulation-flocculation process prior to filtration in the conventional system, the coagulant dosage would need re-adjustment if there were fluctuations on the feed water characteristics and turbidity (Wu & Lo, 2010). Extra cost might incur for further treatment or disposal of the Aluminium residual contaminated sludge which is a common by-product from the conventional systems. The UF system has a distinct advantage over the conventional system in providing consistently high quality of filtrate with direct feed without any coagulant required.

Industrial-scale water treatment plants are important facilities required to provide clean water supply to consumers through the public-piped supply networks. New construction and expansion of these treatment facilities would have immense economic and environmental impacts which entail extensive evaluation and feasibilities studies for long term implications (López-Roldán et al., 2016; Qi & Chang, 2013). This case study has gathered sufficient data to point out that even though the UF system is currently considered an "expensive" technology compared to the conventional system, it has distinctive advantages in terms of consistent filtrate quality and "uncontaminated" sludge discharged compared to the latter. The estimated operation cost (chemicals, electricity and maintenance cost) for the UF system was USD 90, 406/year while the conventional system was USD 43, 560/year based on data from Table 4.2, 4.3, 4.4 and 4.6. Table 4.7 summarized all the findings, literature information and comparison between the two systems in this case study.

No.	Aspects	UF system	Conventional media filtration	Information from literature	Findings from case study	
1.	1. Capital cost Actual construction cost in 20 was 265 USD/m <sup>3</sup> of area was 0 m <sup>2</sup> /m <sup>3</sup> of		Estimated construction cost in 2013 was 251 USD/m <sup>3</sup> of capacity. Required land area was $0.125$ m <sup>2</sup> /m <sup>3</sup> of capacity	UF systems were commonly deemed to require higher construction cost but lesser land area (Pearce, 2007b).	UF systems construction cost was 5.6% higher but utilize only 30% land area compared to the conventional system	
2.	Operational cost	Total operational expenditure was USD 35.37/1, 000 m <sup>3</sup> of treated water	Total operational expenditure was USD 11.04/1, 000 m <sup>3</sup> of treated water	UF system incurred higher cost than conventional system under acceptable feed water conditions (Bonnelye et al., 2008)	Sensitivity analyses has shown that if electricity could be generated by lower cost and chemical cost continue to escalate due to general worldwide inflation, the UF system operational cost would be comparable to the conventional system	
3.	Maintenance cost	Estimated maintenance cost at 5, 200 USD/year	Estimated maintenance cost at 1, 600 USD/year	The UF system is a pressure driven process which requires higher maintenance cost (Bonnelye et al., 2008)	Less attention was required for the UF system because of the automated process. Operators spent substantially more time and efforts to attend the operation of the conventional system	
4.	Filtrate quality	Direct filtration without any coagulant. Consistent filtrate turbidity of less than 1 NTU	ACH was required for coagulation- flocculation prior to filtration. Filtrate turbidity fluctuate between 1 to 4 NTU	Conventional media filtration system requires chemical in the coagulation- flocculation process for efficient solid- liquid separation (Wu & Lo, 2010). It has been reported that consistent good quality of filtrate was observed from the UF systems (Guastalli et al., 2013)	The UF system could produce consistent good quality of filtrate even with fluctuations of the feed water. The conventional system would require proper re-adjustment of the coagulant dosage to achieve good results.	
5.	Water losses	Total water losses were 11.1%. The sludge contained no residual of Al	Total water losses were 6.6%. The sludge contained high Al residual (58 mg/L)	In the conventional system, a total water losses of less than 7% is acceptable (Kawamura, 2000; Tantawy, 2015). In some UF systems, up to 13.3% water losses have been reported (Bai et al., 2013)	The water losses were much higher in the UF system compared to the conventional system. Sludge from the conventional system was contaminated with Al residual and poses health hazard.	

<b>Table 4.7:</b>	Summary	of various	aspects in	the case	study
	•				•

## 4.6 Summary

In this case study, five aspects of both the industrial-scale UF and conventional water treatment systems were evaluated and compared. The commercial aspects have shown that the UF system was a much "expensive" technology in comparison with the conventional system. Total water losses from the UF system were also significantly higher than the conventional system. Apparent advantage of the UF system was displayed through its consistent filtrate quality which exceeds the conventional system. The sludge or by-products from both system were analyzed and indicated high Aluminium residual contaminated sludge from the conventional system compared with the uncontaminated and more environmentally friendly sludge from the UF system. Sensitivity analyses in this case study have indicated that the UF system could be made similar viable as the conventional system in a few scenarios. This case study has a feasible technology in the near future.

### CHAPTER 5:

# KEY ISSUES OF ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM SCALE-UP FROM LABORATORY AND PILOT-SCALE EXPERIMENTAL RESULTS

In the previous two chapters, detailed case studies on industrial-scale UF membrane water treatment system operational issues and the comparison against the conventional system were highlighted. Before commencing the design of an industrial-scale UF membrane system, engineers require relevant and accurate preliminary data to determine the sizing/capacities of the components and equipment. Typically, these preliminary data is obtained through laboratory and pilot-scale experimental studies. The data analyses from these experimental studies become an essential part of designing an efficient industrial-scale UF system. Even after the completion of an UF membrane water treatment plant, both laboratory-scale and pilot-scale systems could still be utilized to study various aspects of the UF process which exhibits similar patterns with the industrial-scale systems.

## 5.1 Introduction

In this chapter, another case study has been conducted on three UF systems which were of different capacities to represent laboratory-scale, pilot-scale and industrial-scale systems. These UF systems were analyzed to determine the differences and similarities of the operational results. Similar UF membrane and river water have been utilized in the operations of all the systems to ensure same operational conditions. Results were compared between all three systems in various aspects such as analysis of filtrate quality, TMP of membrane modules and the electricity utilization. Knowledge gained from these comparisons is important to ensure accurate interpretation of data to scale-up an industrial-scale UF system from the experimental results derived from the laboratory-scale and pilot-scale systems.

#### 5.2 Background

Clean and uncontaminated drinking water is important to human survival as water related diseases has caused thousands of human deaths every day around the world (Misra & Singh, 2012). Developing countries encountered higher risk of facing water crisis with serious health implications due to the increasing population density and the lack of proper infrastructures (Enders et al., 2015). In order to produce consistent and higher quality of drinking water to accommodate the demand, large-scale membrane technology such as UF has becomes a viable option. UF system have been known to be the ultimate barrier to segregate viruses and bacteria in the production of drinking water (Di Zio et al., 2005). Since 1960, utilization of polymeric membranes such as Polyethersulfone (PES) have garnered a wide acceptance in drinking water treatment systems as it is capable of producing consistent quality of filtrate at competitive cost (Tang et al., 2016a).

Regulatory requirements for safe drinking water have become more stringent to avoid contamination crisis. These demands led many water service providers to utilize highly efficient membrane technology such as UF to produce better quality of drinking water (Peiris et al., 2013). Besides being able to produce consistently high quality of filtrate, membrane technologies have also been reported as an effective green design particularly for municipal/urban implementations for their eco-friendliness, costeffectiveness and user-friendliness (Rashidi et al., 2015). Membrane technology has immense potential to alleviate shortages of potable water supply in many parts of the world. Under normal circumstances, industrial-scale water treatment systems efficiency in contaminant removal differs due to the raw water characteristics, engineering design and operational conditions of the systems (Lohwacharin et al., 2014). Typically before the commencement of the design for a full-scale/industrial-scale UF system, preliminary laboratory experiments or pilot-scale studies were conducted to gather the required data (Keeley et al., 2012). Literature has reported that laboratory-scale experiments have provided essential information on the most efficient membrane configuration and operational conditions for UF systems (Howe et al., 2007). In another research, a pilot-scale system was utilized to investigate the performance of an UF system at the Oosterschelde estuary, Netherland (Alhadidi et al., 2012). Both laboratory-scale and pilot-scale studies provide feed water source.

Engineering system scale-up has been considered a challenging task that requires proper care and meticulous revisions (Rossetti & Compagnoni, 2016). The conception of an industrial-scale UF membrane water treatment system involves the reliability of the preliminary data for the detailed engineering design. Design engineers require these data to provide a reliable and functioning industrial-scale UF system (Kim & Lee, 2016). In general, preliminary data from laboratory-scale and pilot-scale studies formed the essential basis of the industrial-scale system design. Detailed analyses have been conducted on three different scales of UF systems under this study to determine the similarities and differences of the operational parameters.

### 5.3 Methodology

In this third case study, operational results from three types of UF system in various capacities to represent laboratory-scale, pilot-scale and industrial-scale have been

analyzed. All these three UF systems were utilizing the same modified Polyethersulfone (mPES) hollow fibre UF membrane manufactured by the same company (Inge GmbH, Germany). The feed water for all the UF systems originates from the same river water source. The same industrial-scale UF membrane water treatment system mentioned earlier in the previous two chapters was again analyzed in this research. In order to maintain the same operational conditions, all the three systems were operated under dead-end constant flux filtration mode with periodic backwash sequences in between. All these 3 systems have been operated with the same feed water from the river. Similar filtration and backwash durations were applied on all the systems. Essential operational data from these systems were recorded and analyzed accordingly to determine the similarities and differences. Each UF systems were equipped with pressure transmitters/gauges to record the TMP. Filtration and backwash flux rates were measured volumetrically or through installed flowmeters. Laboratory analysis using pH and turbidity analyzers were utilized to analyze the feed water and filtrate samples. Electricity parameters such as voltage and ampere to the UF feed pumps were measured using digital multi-meter to determine the electricity utilization.

Detailed analysis of all the data collected from the three UF systems were conducted and compiled accordingly. These data have been critically examined against literature reports for a comprehensive study of the results obtained. Aspects such as filtrate quality, TMP of membrane modules and electricity utilization of the three UF systems have been further elaborated in the subsequent sections. Figure 5.1 shows the actual photograph of the three UF systems under this case study.





Figure 5.1 (a) Laboratory-scale UF system

Figure 5.1 (b) Pilot-scale UF system



Figure 5.1 (c) Industrial-scale UF system

## Figure 5.1: Three UF systems utilized for the case study

## 5.4 Results and discussions

All three UF systems were put into operation with the same type of UF membrane and feed water source. Three different types of UF membrane modules (consisting the same type of hollow fibre membranes) with various membrane surface area were used. Table 5.1 shows the capacity and operating conditions of all these three systems. All these UF systems were operating under the same filtration flux to ensure uniformity.

Parameters	Laboratory-scale	Pilot-scale	Industrial-scale
Feed water	River water	River water	River water
UF membrane mPES hollow fibre		mPES hollow fibre	mPES hollow fibre
Membrane surface 1.0 m <sup>2</sup>		$6.0 \text{ m}^2$	7, 200 m <sup>2</sup>
Filtration flux	80 L/m <sup>2</sup> hr	80 L/m <sup>2</sup> hr	80 L/m <sup>2</sup> hr
Feed water flow	80 L/hr	480 L/hr	576, 000 L/hr

Table 5.1: Operating conditions of the three UF systems

Figure 5.1 and Table 5.1 illustrated the actual size and operational capacities of the three UF systems. All these systems were evaluated on their respective filtrate quality, TMP through membrane modules and the specific electricity utilization which have been further elaborated in the subsequent sections.

## 5.4.1 Analysis of filtrate quality

Experiments were conducted with the laboratory-scale and pilot-scale systems while actual operational data were extracted from the in-house laboratory analysis of the industrial-scale system for further evaluation. As mentioned earlier, all the UF systems were utilizing the same mPES hollow fibre membrane and taking the same river source as feed water to ensure uniformity. The initial feed water parameters such as turbidity, colour and pH were analyzed. Filtrate after the UF process from each systems were analyzed for these same parameters which represent the physico-chemical properties of the filtrate quality (Roig et al., 2014). Table 5.2 shows the results of filtrate from the three UF systems under similar operational conditions as well as the feed water samples analyses. The analysis results indicated that all the three UF systems produced similar high quality of filtrate with less than 0.20 NTU and with detected colour lower than 15

Pt – Co. Since there was mainly solid-liquid physical separation in the UF process, the pH of the feed water and filtrate were expected to be quite similar without much variation. These results indicated that for UF systems, the laboratory-scale and pilot-scale studies would produce almost similar filtrate results as an industrial-scale system.

Parameters	Laboratory-scale	Pilot-scale	Industrial-scale	
Feed water turbidity	23 NTU	23 NTU	23 NTU	
Feed water colour	56 Pt – Co	56 Pt – Co	56 Pt – Co	
Feed water pH	7.3	7.3	7.3	
Filtrate turbidity	0.15 NTU	0.18 NTU	0.19 NTU	
Filtrate colour	< 15 Pt – Co	< 15 Pt – Co	< 15 Pt – Co	
Filtrate pH	7.1	7.2	7.1	

Table 5.2: Feed water and UF filtrate analysis results

Literature has reported that a pilot-scale membrane system was used at Kwai Chung industrial wastewater pumping station at Hong Kong to verify and substantiate further upgrading of an existing industrial-scale system (Guan et al., 2014). In another different study, a laboratory-scale membrane system was set-up to determine the filtrate quality using seawater from the Mediterranean Sea off the coast of Gruissan, France (Monnot et al., 2016). These were practical examples whereby the pilot-scale and laboratory-scale systems were used to determine the filtrate quality for the proposed industrial-scale systems. In general most literature has reported laboratory-scale or pilot-scale membrane systems were utilized to determine the filtrate quality based on the intended feed solutions as a basis. In this study, the data shown in Table 5.2 concurred with the suggested literature common practice in using the pilot-scale and laboratory-scale membrane systems filtrate results as a good approximation to a full-scale system.

### 5.4.2 Trans-membrane pressure of membrane modules

The trans-membrane pressures (TMP) from all the three systems under similar operational condition stated in Table 5.1 and Table 5.2 have been recorded. Results in Table 5.3 indicated that the TMP of all three systems were not very consistent. Both the laboratory-scale and pilot-scale systems recorded much higher TMP than the industrialscale system. The cause of this discrepancy might have originated from the UF membrane modules design. Most small-scale UF membrane modules were not hydrodynamically optimized to ensure lower manufacturing cost in order for more competitive pricing. These small-scale systems often do not require such high-end optimized membrane modules as the production volume was small. The membrane manufacturer (Inge GmbH, Germany) for all UF systems in this case study only produced central core UF membrane modules for small-scale systems specifically cater for laboratory experiments and pilot plants. This membrane manufacturer produced a more hydro-dynamically optimized industrial-scale UF module known as annular gap configuration to reduce the hydraulic pressure losses within the module itself. Figure 5.2 illustrates the different arrangement of the hollow fibre membranes of the annular gap and the central core UF membrane modules.

Ta	ble 5.3: A	lverage	TMP	of UF	systems	under	similar	operational	conditions
					•			1	

Parameters	Laboratory-scale	Pilot-scale	Industrial-scale
UF module design	Central core	Central core	Annular gap
TMP	0.41 Bar	0.42 Bar	0.32 Bar



Figure 5.2: Annular gap (left) and central core (right) hollow fibre configurations of UF membrane modules

Literature has reported that the UF membrane modules geometry incurred various velocities fields and pressure drops (Cano et al., 2013). These membrane modules design causes various type of pressure losses within the module itself and a more hydro-dynamically optimized module would have less pressure losses. The UF membrane modules manufacturer of this case study has claimed that the annular gap configuration design was more optimized to allow lower pressure drop which reduces energy consumption for UF in large-scale systems. Figure 5.3 shows the TMP profiles for all the three UF systems operating under the same conditions. Both the laboratory-scale and pilot-scale systems exhibited almost similar TMP profiles pattern and values which were between 0.34 - 0.42 Bar. The industrial-scale system indicated much lower TMP values of between 0.25 - 0.32 Bar even though the TMP profile pattern was similar to both the experimental systems. Similar TMP differences were also observed by other researchers between industrial-scale and pilot-scale membrane systems although the

TMP profiles pattern were the same (Kamp et al., 2000). All the systems were operating under filtration sequence for 30 minutes with an intermittent backwash of 60 seconds.



Figure 5.3: TMP profiles of UF systems

A distinctive difference between the two experimental systems (laboratory-scale and pilot-scale) and the industrial-scale UF system was the UF membrane modules design shown in Table 5.3 and Figure 5.2. Both the experimental systems were utilizing central core UF membrane modules while the industrial-scale system was installed with annular gap UF membrane modules. The UF membrane modules manufacturer has claimed that the annular gap configuration was much more hydro-dynamically optimized than the central core configuration and allows lower pressure losses.

As more hollow fibre membranes were packed into membrane modules, the hollow fibre networks interact during filtration and causes additional pressure losses compared to a single strand of hollow fibre membrane (Kostoglou & Karabelas, 2008). The filtration flux for all three UF systems was operated at 80 L/m<sup>2</sup>hr as shown in Table 5.1. Higher TMP observed on the central core configuration UF modules was most likely caused by the hydraulic interaction on hollow fibre networks and the modules geometry. It is not economically viable to produce hydro-dynamically optimized annular gap membrane modules when there are only a low number of hollow fibre membranes packed in these small modules. After the filtration sequence, all the three UF systems were cleaned under the same backwash condition with 230 L/m<sup>2</sup>hr water flux for 60 seconds before the next filtration sequence commences.

### 5.4.3 Electricity utilization

It was mentioned earlier that the pressure driven UF system is an energy intensive process. Electricity utilization during filtration is an important commercial aspect for the pressure driven UF system. One of the most significant costs of UF system is the electricity utilized to operate the feed pumps. UF systems with higher TMP during filtration would require more electricity power to drive the motor of the pumps. The correlation between electricity power required and the pressure of the system has been shown in equation (3.1) at Chapter 3. It was discussed in previous sections that the annular gap membrane module design for the industrial-scale system was more hydrodynamically optimized compared to the smaller central core membrane modules. Both of the experimental systems (laboratory-scale and pilot-scale) utilizing central core membrane modules exhibited higher TMP compared to the industrial-scale system under similar operational conditions.

Another aspect besides the TMP which affects the electricity utilization of any pressurized system is the feed pump efficiency (Meng et al., 2017). Equation (5.1) shows the correlation between the overall pump efficiency against operating flow rate or
Q (m<sup>3</sup>/s), operating pressure or H (Pascal) and the electricity power requirement or W (Watt) for the feed pumps. Measurements and analyses were conducted on the feed pumps of the experimental systems to determine the pump efficiency based on equation (5.1). The feed pumps were operated under constant motor speed at certain pressure (measured with pressure gauge) and the flow rates were determined volumetrically. Electricity current and voltage to the pumps were measured with digital multi-meter to ascertain the power requirement of the pumps during operation. Table 5.4 shows the feed pumps motor ratings, operating conditions of the feed pumps, estimated feed pump efficiency and the specific electricity utilization for all the three UF systems.

$$Pump \ efficiency = \frac{Q \ X \ H}{W}$$
(5.1)

	Laboratory- scale	Pilot-scale	Industrial-scale
Pump motor rating	0.38 kW	0.70 kW	65 kW
Actual power consumed	0.31 kW	0.60 kW	61 kW
Pump operating pressure	3.25 Bar	3.25 Bar	3.25 Bar
Pump operating flowrate	0.47 m <sup>3</sup> /hr	1.77 m <sup>3</sup> /hr	580 m <sup>3</sup> /hr
Feed pump efficiency	14%	27%	87%
Specific electricity utilization	0.66 kWh/m <sup>3</sup>	0.34 kWh/m <sup>3</sup>	0.11 kWh/m <sup>3</sup>

Table 5.4: Feed pumps operational conditions and estimated efficiency

The normal operating pressure of the industrial-scale UF membrane water treatment system feed pump was 3.25 Bar to cater for pressure losses of all the static and dynamic heads to the elevated treated water storage tank. Both the feed pumps of the

experimental systems were operated at similar operating pressure to determine the respective flow rates. Based on equation (5.1) the feed pumps efficiencies were estimated and shown in Table 5.4. Data shown in Table 5.4 indicated the laboratory-scale feed pump has the lowest efficiency at 14% while the industrial-scale feed pump has the highest efficiency at 87%. The specific electricity utilization of the industrial-scale feed pump at 0.34 kWh/m<sup>3</sup> and finally the highest for laboratory-scale feed pump at 0.66 kWh/m<sup>3</sup>.

Literature has reported that most high-capacity pumps or motor rating above 0.75 kW was much more energy efficient than the smaller pumps (Sauer et al., 2015). Typically these small capacity pumps or motor with less than 0.75 kW has very low energy efficiency of less than 40% only (Skrzypacz, 2014). In Table 5.4 it has been shown that the industrial-scale feed pump with motor rating of 65 kW has the highest energy efficiency at 87%. The laboratory-scale feed pump with motor rating of 0.38 kW has the lowest efficiency at only 14% follow by the pilot-scale feed pump with motor rating of 0.70 kW at 27%. All the data shown in Table 5.4 has indicated that higher pump efficiency would require less energy/electricity to produce a unit of filtrate from the UF systems.

## 5.5 Scaling-up industrial-scale systems based on experimental data

This case study has highlighted the similarities and differences obtained through the three UF systems under the same operational conditions. The results shown in this case study provide some interesting data on the accuracy and limitations of the laboratory-scale and pilot-scale systems to represent the actual industrial-scale UF system. Industrial-scale UF systems often incurred very high capital expenditure and precise engineering design is essential to ensure minimal deviations from the required outputs.

The experimental systems (laboratory-scale and pilot-scale) allowed a much lower cost to develop in order to gather essential data for scaling-up the UF system.

Both the experimental systems provide preliminary design data to scale-up an industrial-scale UF system on a lower budget. Researchers have agreed with the fact that higher expenditure cost for system set-up and sampling would provide much higher accuracy estimation of the process (De Groote & Traoré, 2005). The compatibility between the feed water source and the UF membrane to produce the desired filtrate quality is one of the main concerns in scaling-up an UF system. Subsequently design engineers are required to evaluate the energy utilization of the UF system to determine the operational cost.

The fluctuating feed water characteristics pose a serious problem to the operation of industrial-scale UF systems. Characteristic changes and suspended solids concentrations in the feed water would require adjustment of the filtration flux rate and more frequent backwash sequences to reduce the membrane fouling. The increase of TMP during filtration reflects higher electricity utilization which relates to the operational cost. In this case study, the pilot-scale system provides much closer simulation results in term of both filtrate quality and specific electricity utilization for the industrial-scale system under similar operational conditions. Although the laboratory-scale system provides very similar filtrate quality results to the industrial-scale system, it has much more limitations on the estimation of the specific energy required for an industrial-scale system. The cost to build the pilot-scale system was much higher than the laboratory-scale system in this case study.

Results obtained in Table 5.2, Table 5.3 and Table 5.4 have indicated that certain assumptions would need to be established in order to scale-up an industrial-scale system from pilot-scale and laboratory-scale experimental results. Case study conducted by other researchers in the Netherlands has shown that there were significant differences in

absolute TMP values for the pilot-scale and industrial-scale systems but exhibited similar TMP profiles pattern (Kamp et al., 2000). Similar findings were obtained in this case study whereby the TMP during filtration for both the laboratory-scale and pilotscale systems were much higher than the industrial-scale system under same operational conditions but the TMP profiles exhibited similar patterns as shown in Figure 5.3. In order to ensure the design filtration flux of 80 L/m<sup>2</sup>hr is achieved, a variable speed drive (VSD) is recommended to be installed to control the motor speed of the feed pump. The induction motor speed controlled by a VSD enables reduction of electricity utilization by regulating the motor speed to achieve the required duty point of the pump (Al-Bassam & Alasseri, 2013). Results obtained in this case study have shown that the TMP of the industrial-scale system under the same operational conditions was much lower than both the pilot-scale and laboratory-scale systems. This would suggest that installing a VSD to regulate the feed pump would allow the pump to operate at a much lower speed to sustain the lower TMP required. Without such VSD installed, the feed pump would be operating at nominal speed which might incurred much higher filtration flux than the required design. Throttling the discharge valve of the feed pump is usually the solution to reduce the flux but a lot of energy is wasted through the pressure losses of throttling the valve. A better and more efficient solution to achieve the design flux is to regulate the motor speed via VSD control.

Filtrate quality remains one of the most important parameter in membrane systems. The UF process needs to produce the desired filtrate quality based on the feed water characteristics. In this case study, both the laboratory-scale and pilot-scale systems were producing similar filtrate quality (in terms of turbidity and colour) as the industrial-scale system. The quality of the filtrate obtained through both experimental systems using the same feed water source provides accurate prediction of the filtrate quality in an industrial-scale system. These accurate predictive results allow the industrial-scale UF system operator to rapidly detect any discrepancy in the filtrate quality by conducting a laboratory-scale filtration experiments with the same feed water. Any UF membrane fibre breakages or valve leakages in the industrial-scale system could be determined if the filtrate quality results in the laboratory were much better. If filtrate turbidity was much higher in the industrial-scale system compared to the laboratory-scale system, this usually indicates membrane fibre breakages or mechanical equipment malfunction such as leaking valves.

In this case study, both the laboratory-scale and pilot-scale systems results have also provided operational cost estimation of the industrial-scale UF system. Data presented in Table 5.4 indicated much lower specific electricity utilization on the industrial-scale system feed pump (0.11 kWh/m<sup>3</sup>) compared to the laboratory-scale (0.66 kWh/m<sup>3</sup>) and pilot-scale (0.34 kWh/m<sup>3</sup>) systems. The main reason for the differences in electricity utilization for the three UF systems was caused by the various efficiencies of the feed pumps. Literature has reported that an industrial-scale UF membrane water treatment system usually requires specific energy of about 0.20 kWh/m<sup>3</sup> (Pearce, 2008). The industrial-scale UF system in this case study has shown much lower specific energy requirement than literature reports because only the feed pump electricity utilization was taken into consideration. Higher TMP during filtration would results in higher energy utilization to drive the motor of the feed pump. The central core UF membrane modules for the experimental systems have shown higher TMP than the industrial-scale annular gap membrane module under similar operational conditions. Both the laboratory-scale and pilot-scale systems have provided a rough estimation of the specific energy requirement of the industrial-scale system. It is presumed that the industrial-scale system would require much lower specific electricity utilization during operation compared to both the experimental systems due to higher feed pump

efficiency and lower TMP in the industrial-scale UF membrane modules. Table 5.5 summarized all the relevant characteristics of the three UF systems in this case study.

		Laboratory- scale	ooratory- Pilot-scale Industria scale scale		Comments
	Filtrate quality	0.15 NTU, <15 Pt-Co, pH 7.1	0.18 NTU, <15 Pt-Co, pH 7.2	0.19 NTU, <15 Pt-Co, pH 7.1	Literature has reported both laboratory-scale and pilot- scale system were utilized to determine the filtrate quality as projection for membrane systems scale-up (Guan et al., 2014; Monnot et al., 2016).
	UF module design	Central core	Central core	Annular gap	Interaction between hollow fibre networks and the membrane module geometry has significant effect on the pressure drop of the system (Cano et al., 2013; Kostoglou & Karabelas, 2008).
	TMP	0.41 Bar	0.42 Bar	0.32 Bar	Similar TMP values differences were also observed by other researchers between pilot- scale and industrial-scale systems although the TMP profiles pattern were the same (Kamp et al., 2000).
	Feed pump motor rating and efficiency	0.38 kW, 14%	0.70 kW, 27%	65 kW, 87%	Literature has reported that motors and pumps with very low power rating were usually less efficient (Sauer et al., 2015; Skrzypacz, 2014).
	Specific electricity utilization	0.66 kWh/m <sup>3</sup>	0.34 kWh/m <sup>3</sup>	0.11 kWh/m <sup>3</sup>	Due to lower feed pump efficiency, both the experimental systems have higher specific electricity utilization. A typical industrial-scale UF system should be operating at about 0.20 kWh/m <sup>3</sup> (Pearce, 2008).

 Table 5.5: Summary of the three UF systems results

# 5.6 Summary

Prior to the construction of an industrial-scale UF membrane water treatment plant, experimental set-up such as pilot-scale and laboratory-scale systems are often established. These experimental systems are utilized to collect the necessary design parameters and the expected filtrate quality from a specific feed water source. This case study has highlighted how the data obtained through laboratory-scale and pilot-scale studies could be interpreted to scale-up the system with much higher accuracy and precise information extraction. The results from both the experimental systems (laboratory-scale and pilot-scale) indicated that the filtrate quality were a good representation of an industrial-scale system under the same operational conditions. Although the TMP and specific electricity requirements were much higher in both the experimental systems, the causes have been identified. Even though the absolute values of the TMP differ, all three UF systems exhibited similar TMP profiles pattern. This enables the experimental systems to be utilized for the study of TMP profiles pattern anticipated in an industrial-scale UF system under similar operational conditions.

#### CHAPTER 6:

# POTENTIAL MEMBRANE FOULING PARAMETERS PREDICTION USING HYBRID MODELLING FOR ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM

Membrane fouling prediction is a critical operational issue and many comprehensive studies on this subject have been conducted using advanced analysis methods (Cheng et al., 2016). Fluctuations of feed water characteristics are some of the main causes for membrane fouling in the industrial-scale UF membrane water treatment plants. Early detection or predictions of potential membrane fouling operational conditions are essential to ensure minimal future complications and operational cost escalations. Results obtained in Chapter 5 has indicated the TMP profiles pattern exhibited by both experimental systems were similar with the industrial-scale UF system. This enables the utilization of UF experimental systems to study the TMP profiles for future implementation on industrial-scale system with some minor adjustment on the absolute TMP values.

# 6.1 Introduction

Predictive models provide important information of the filtration process which is crucial for efficient operation of UF membrane water treatment systems. Such information allows mitigation actions to be taken during high potential membrane fouling conditions caused by feed water characteristics changes. Due to limitations of available facilities and resources in a typical UF membrane water treatment plant, extensive and in-depth laboratory analyses of the potential membrane fouling parameters are seldom conducted in-house. Predictions or estimations of these parameters based on commonly available data and equipment from these water treatment plants are viable alternative solutions to cater for such requirements. In this chapter, a practical hybrid modelling approach has been utilized to predict two potential membrane fouling parameters in the dead-end constant flux UF process.

# 6.2 Background

There were many successful examples of industrial-scale UF membrane water treatment plants reported in literature (Laîné et al., 2000; Monnot et al., 2016). Filtrate quality from UF systems have surpassed the common regulatory requirements such as total suspended solids (TSS), turbidity, virus and bacteria removal (Kim et al., 2011). Since the past decade, UF has been considered as one of the most significant advanced technology for water treatment systems in many countries (Huang et al., 2008). The two most common drawbacks of UF systems are the higher cost involved (Bonnelye et al., 2008; Massé et al., 2011; Pearce, 2007b) and the membrane fouling problems (Guo et al., 2012; Shirazi et al., 2010; Thekkedath et al., 2007; Wang et al., 2014). In order to address these problems, the modelling of membrane filtration process has become an exciting and rigorous research area to ensure optimum operational conditions (Llanos et al., 2013).

Theoretical or first principle modelling is one of the most commonly utilized tool to represent membrane filtration processes (Saleem et al., 2017). Many researchers have proposed various fundamental membrane filtration models through laboratory experimental validation or pilot-scale studies (Guo et al., 2012; Kim & DiGiano, 2009; Tien et al., 2014). Most of these models proposed the use of Darcy's law to establish correlation between filtration resistance, flux and TMP. Particles accumulation and

deposition on the membrane surface causes higher resistance which raised the TMP under constant flux filtration. In order to ensure a predictable and consistent build-up of the fouling layer during filtration, most laboratory experiments utilized simulated feed solutions with known concentrations of the solids contents (Sioutopoulos & Karabelas, 2012; Tian et al., 2013b; Yi et al., 2013). These ideal conditions of having feed solutions with consistent characteristics and solids concentrations are rarely available in typical industrial-scale UF membrane water treatment plants. Feed water to these water treatment plants commonly originates from rivers which have tendency to change characteristics and turbidity abruptly especially during heavy rainfalls conditions (Davies & Mazumder, 2003; Lee et al., 2016a).

Darcy's law is based on cake filtration model which is one of the most widely used theoretical model for process design and modelling (Xu et al., 2008). Literature has reported that the accumulation of the solids as cake layer increases the TMP during constant flux filtration (Chen et al., 1997). Solids content in the feed water becomes consolidated cake structure on the membrane surface which causes fouling and reduces the flux under constant pressure filtration (Castaing et al., 2010; Pontié et al., 2012). It was reported that compressible cake filtration model was the most likely mechanism to describe the dynamic deposition of protein molecules in dead-end UF systems (Iritani et al., 2002). The cake filtration model is one of the most widely accepted model to describe the membrane fouling process (Han et al., 2017). Cake layer formation and accumulation is known to be a complicated dynamic process which ultimately causes membrane fouling (Zhou et al., 2015). In general, natural surface water sources contain organic matters which become highly compressible cake layer during filtration (Bugge et al., 2012). Specific cake resistance is a commonly used parameter to express the characteristics of the cake layer (Khan et al., 2009). This parameters is highly

dependence on the feed water characteristics which affect the cake layer permeability and porosity (Park et al., 2006).

Specific energy utilization of dead-end filtration operation mode is typically less than the cross-flow filtration for large-scale drinking water production (Mendret et al., 2009). The characteristics and structure of the cake layer in dead-end filtration operation mode plays a significant role on the filtration performance. In order to enhance the filtration process, some researchers have suggested selecting an appropriate coagulant to improve the filtration process (Yu et al., 2013). It was reported that most commercial UF membrane water treatment systems operate under dead-end constant flux conditions to ensure consistent filtrate capacity with minimal energy requirements (Pearce, 2007b). Laboratory membrane filtration experimental set-ups reported in literature were commonly conducted under constant pressure conditions as constant flux operations were much more difficult to achieve (Mahdi & Holdich, 2013).

Even though theoretical models utilizing the Darcy's law could provide good accuracy to the actual filtration process, it requires extensive efforts and time to obtain precise values of certain filtration parameters (Boerlage et al., 2004). Most of these parameters relating to the cake layer and feed water characteristics require laborious experimental study to be ascertained. Parameters estimation models provide a good alternative method to rapidly produce reliable results. The utilization of hybrid models were reported to represent the dynamic evolutions of a system that consist of both logical and continuous components (Karelovic et al., 2015). Artificial neural networks (ANN) have been applied as part of a hybrid model to leverage on the advantages of the black box modelling capability to describe statistical data efficiently by some researchers (Nourani et al., 2014). Experimental data has shown high accuracy of an adaptive neuro-fuzzy interference system to model cross-flow UF of oily wastewater (Salahi et al., 2015). ANN and genetic algorithm (GA) were also reported being utilized

in the Tehran Refinery wastewater to estimate filtration flux under various operating parameters and conditions of an UF system (Badrnezhad & Mirza, 2014). The study has shown the combinations of ANN and GA were capable to predict and optimize process inputs to achieve the desired flux rate. Most membrane filtration mechanisms have been reported to be highly unpredictable and requires some estimation method by general models (Sen et al., 2011). Knowledge based hybrid ANN models have shown promising results on UF processes with valid assumptions.

It was reported that ANN models have been utilized to predict TMP profiles of a membrane water treatment system with high accuracy (Delgrange et al., 1998). Relevant inputs parameters such as feed water characteristics were fed as inputs to the ANN model to predict the TMP profiles of the UF process. In a much more elaborate study, two ANN models were combined to estimate parameters for surface water UF (Delgrange-Vincent et al., 2000). Efforts were also taken to develop two interconnected ANN models coupled with the Darcy's law (Cabassud et al., 2002). The ANN models were used to predict the total resistance of the UF and subsequently Darcy's law was utilized to determine the TMP of the filtration process. Multiple feed water input parameters such as dissolved oxygen, turbidity, ultra-violet absorbency and pH were fed into the ANN models. Under experimental conditions, the feed water solids concentrations were more reliable than turbidity to model the membrane filtration process (Foley, 2006). Some researchers have experimentally shown that even though there was a reasonable linear correlation between turbidity and total suspended solids concentrations on natural surface water, but the correlation varies from every catchment locations (Rügner et al., 2014). In another related study on natural surface feed water, laboratory-scale experiments were conducted to compare the capabilities between ANN models and the performance of pores blocking models (Liu & Kim, 2008). The results

in this study have indicated that ANN models have better accuracy and agreement with the experimental data.

The utilization of ANN models were also investigated to optimize operational conditions and predict permeate flux in wastewater systems (Soleimani et al., 2013). Some of the reported advantages of ANN models were adaptability, robustness and simplicity which were suitable for the application in water treatment systems. Reliable simulations results were also obtained in the study of micellar-enhanced ultrafiltration (MEUF) for wastewater (Rahmanian et al., 2011). Laboratory-scale study have shown the capability of ANN models to predict non-linear dynamics processes in wastewater UF systems (Teodosiu et al., 2000). In a another study, pilot-scale experiments were utilized to predict performance of a submerged hollow fibre membrane filtration process (Choi et al., 2012). Besides these laboratory-scale and pilot-scale studies, ANN models were also utilized to predict performance of an industrial-scale waste water treatment plant with the capacity of 1 million m<sup>3</sup> a day at the Greater Cairo district at Egypt (Hamed et al., 2004). The application of ANN has also been reported in optimization of UF membrane fabrication study (Tan et al., 2014). Through the concept of hybrid modelling, the GA and ANN models have been combined to determine the optimized UF membrane preparation conditions. Table 6.1 summarizes some of the applications of ANN in water and wastewater UF processes.

No.	Researchers	Applications of ANN in UF of water/wastewater		
1.	(Cabassud et al., 2002)	Predictive control algorithm was developed and utilized to improve productivity of surface feed water UF.		
2.	(Badrnezhad & Mirza, 2014)	Optimization and modelling with combination of GA and ANN for wastewater UF.		
3.	(Hamed et al., 2004)	ANN models were developed to predict suspended solids concentrations and biochemical oxygen demand for wastewater UF.		
4.	(Delgrange et al., 1998)	ANN model was utilized to predict the TMP of UF in potable/drinking water treatment system.		
5.	(Delgrange-Vincent et al., 2000)	ANN was utilized as recurrent model to predict the productivity of a surface feed water UF pilot plant.		
6.	(Soleimani et al., 2013)	Fouling resistance and permeate flux prediction of wastewater UF tested in laboratory.		
7.	(Liu & Kim, 2008)	ANN and pore blocking UF models performance were compared for surface feed water.		
8.	(Choi et al., 2012)	Using ANN to predict membrane filtration performance on submerged hollow fibre pilot-scale membrane system.		
9.	(Rahmanian et al., 2011)	Wastewater permeate flux and rejected metal ions prediction in MEUF laboratory experiments.		
10.	(Tan et al., 2014)	Utilizing GA and ANN for optimization of UF membrane fabrication process.		
11.	(Teodosiu et al., 2000)	Flux prediction during UF and after backwashing of wastewater in laboratory experiments was conducted in this work.		

Table 6.1: Applications of	f ANN in water an	d wastewater UF	processes
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Natural surface water originates from rivers are the main feed water sources for most industrial-scale potable/drinking water treatment plants (Davies & Mazumder, 2003). Fluctuation of feed water characteristics due to various causes would affect the operation of UF membrane water treatment plants which might increase the likelihood of membrane fouling. It has been shown in research studies that the inconsistency of feed water characteristics incurred severe impact on the filtration efficiency of membrane systems (Choi & Kim, 2015). The subsequent sections in this chapter further elaborates on the hybrid modelling approach of this study which enables parameters prediction related to potential membrane fouling propensity.

# 6.3 Methodology

A pilot-scale UF system has been designed and commissioned to gather the required experimental data to develop a practical hybrid model for parameters prediction of the dead-end constant flux UF water treatment process. This was the same pilot-scale UF system utilized in the previous case study in Chapter 5. Both experimental and software simulation studies were conducted to develop the process model. Laboratory experiments and data collection with the pilot-scale UF system was conducted with feed water originates from a natural surface water source. This pilot-scale UF system was placed at the industrial-scale UF membrane water treatment plant discussed earlier in the previous case studies and fed with the same river water. The data collected was utilized to train the ANN model using computer software. Further elaboration on the detailed methodology has been highlighted in the following sections of this chapter.

#### 6.3.1 Data collection and water sample analysis for the model

Actual filtration data using the river water source as feed water was recorded from experimental studies of the pilot-scale UF system. This pilot-scale system consists of the same hollow fibre UF membrane utilized in the industrial-scale UF membrane water treatment plant discussed in the previous case studies. The UF membrane module known as Dizzer P 4040-6.0 (manufactured by Inge GmbH, Germany) for the pilot-scale UF systems was much smaller with only 6 m<sup>2</sup> of membrane surface area. Figure 6.1 shows the actual and schematic diagram of the pilot-scale UF system used for the data collection and experiments.



Figure 6.1 (a): Actual pilot-scale UF system



Figure 6.1 (b): Schematic diagram of the pilot-scale UF system Figure 6.1: Actual and schematic diagram of the pilot-scale UF system

The UF pilot-scale system in Figure 6.1 resembles closely the industrial-scale UF membrane water treatment plant which operates under dead-end constant flux filtration mode in the previous case studies. In order to ensure constant flux filtration was maintained, variable area flowmeters and manual valves were installed on the pilot-scale UF system to regulate the feed water flow into the UF membrane module. The

inlet and filtrate ports of the UF membrane module were equipped with pressure transmitters to determine the TMP during filtration. Filtration duration data was recorded manually while the feed water turbidity was analyzed using laboratory turbidity analyzer. The TMP during filtration sequence was recorded every 5 minutes until 60 minutes was reached. All the experiments with the pilot-scale system were conducted under dead-end filtration mode with flux rate of 80 L/m<sup>2</sup>hr. After every filtration sequence, a hydraulic backwash with 230 L/m<sup>2</sup>hr of flux rate was initiated to clean the UF membrane module. These were the same filtration and backwash flux rates applied on the industrial-scale UF membrane water treatment plant mentioned in the previous case studies. Each 60 minutes filtration sequence on the pilot-scale UF system only requires less than 0.5 m<sup>3</sup> of feed water volume from the river. It has been reported that filtration processes of natural surface water were complicated due to the variation of constituents presence in the water (Delgrange-Vincent et al., 2000).

Laboratory analyses of the feed water and filtrate samples were an essential part of the data collection in the process modelling. Most water treatment plants utilize inhouse laboratory analysis of their water samples on a daily basis. Turbidity of water samples are often analyzed instead of the solids concentrations of the samples as it is much easier and faster to analyze the former. Membrane filtration model utilizing the Darcy's law incorporates the solids concentrations of the feed water as part of the equation (Foley, 2006). The analysis of the solids concentrations of water samples might require more than 10 hours for an accurate reading in accordance to American Public Health Association (APHA) analysis method. In order to simplified the estimation of the water samples solids concentrations, a correlation between turbidity and solids concentrations of the samples were often established for surface water catchment area (Rügner et al., 2014). All the relevant data collected through the pilot-scale UF system and laboratory analysis were compiled digitally to model the filtration process using simulation software. Initially all the relevant data was organized to develop a hybrid model which consists of an ANN model and Darcy's law. Subsequently the simulation results from the hybrid model were verified against experimental data to validate its accuracy. The ANN model was utilized to predict filtration parameter known as specific cake resistance or  $\alpha$ . This parameter was then substituted into the theoretical filtration model using Darcy's law to determine the feed water solids concentrations or  $c_s$ . Laboratory analysis of the feed water solids concentrations data was then utilized to validate the simulated results. This hybrid model provides estimation of the essential filtration parameters such as specific cake resistance during filtration and solids concentrations of the feed water. The hybrid model is intended to be used as an alternative estimation method of these parameters which differs from the conventional method with laborious experimental studies using specific equipment which is seldom available in an industrial-scale UF membrane water treatment plant in-house laboratory.

# 6.3.2 Hybrid modelling procedures

The hybrid model in this study consists of an ANN model and a theoretical first principle model (Darcy's law). Under this study, the main intention of developing this hybrid model is to provide a rapid prediction or estimation method of the filtration parameters. The estimation of the specific cake resistance ( $\alpha$ ) during filtration was achieved by utilizing the ANN predictive model with relevant inputs data. Based on the estimated values of  $\alpha$  from the ANN predictive model, the first principle/conventional cake filtration model was used to estimate the feed water solids concentrations ( $c_s$ ). The rational in developing this hybrid model (consisting both ANN and first principle models) was to allow an alternative method of rapidly modelling the membrane filtration process without the specific analysis equipment which is seldom available at the in-house laboratory of a typical industrial-scale UF membrane water treatment plant. Utilizing commonly available on-line and laboratory analysis data (filtration time, TMP and feed water turbidity) for these filtration parameters estimation is a viable alternative method as it only requires minimal cost for implementation. It has been reported that filtration parameters such as  $\alpha$  and  $c_s$  require extensive efforts and time to be determined experimentally with high accuracy (Boerlage et al., 2000). These two parameters provide essential information on potential membrane fouling propensity which allows early warning for water treatment plant operators to take necessary actions. The feed water characteristics changes are beyond the control of the treatment plant operators and ensuring minimal or mitigate membrane fouling due to such changes is an important aspect of the operation.

## 6.3.2.1 Development of first principle model

The development of a practical filtration model is essential to provide early warning of potential membrane fouling propensity due to characteristics changes of the feed water or abnormal operational conditions of the UF system. Besides providing indication of potential membrane fouling propensity, the model is expected to produce these information rapidly as feed water characteristics might changes abruptly within hours. Literature has reported that feed water characteristics is one of the many aspects that affect the membrane filtration process (Ní Mhurchú & Foley, 2006). The first principle model based on Darcy's law is shown in equation (6.1) whereby  $\Delta P$  is the TMP, *J* is the filtrate flux,  $R_m$  is the membrane resistance,  $\mu$  is the filtrate viscosity, *m* is the cake mass per unit membrane area and  $\alpha$  is the specific cake resistance.

$$J = \frac{\Delta P}{\mu(R_m + \alpha m)} \tag{6.1}$$

Validity of this first principle or cake filtration model is justified with literature supports as follow:-

- The Darcy's model is relevant to UF membrane filtration process (Zhou et al., 2015).
- 2. It is a common used model for process design (Xu et al., 2008).
- 3. The model takes into account the specific cake resistance of the filtration process (Park et al., 2006).
- 4. The model is suitable to represent dead-end filtration (Mendret et al., 2009).
- The model also takes into consideration changes of feed water characteristics (Bugge et al., 2012).

The first principle model requires membrane resistance  $(R_m)$  to be determined experimentally prior to the actual filtration process with feed water. A new UF membrane module was utilized and purified water (m = 0) was filtered through the UF membrane module. Data of the filtration flux with purified water  $(J_w)$ , membrane resistance  $(R_m)$  and the respective trans-membrane pressure  $(\Delta P_w)$  were correlated using Darcy's law to form equation (6.2). Details of the filtration procedures have been reported in literature (Boerlage et al., 1998; Pellegrin et al., 2015; Roy & De, 2015) which are commonly utilized to determine  $R_m$  with purified water.

$$R_m = \frac{\Delta P_w}{J_w \mu} \tag{6.2}$$

Specific cake resistance ( $\alpha$ ) is a filtration parameter which has correlation with multiple others parameters such as particle size distribution, particle shape, density, porosity and TMP (Sripui et al., 2011). Since all the experiments in this research were conducted under dead-end constant flux filtration mode, the power-law developed for constant pressure filtration (Sripui et al., 2011) was not suitable. Variation of feed water characteristics and solids concentrations incurred a critical problem to the UF process which requires attention. Correlation between feed water solids concentrations and filter cake mass is shown in equation (6.3).

$$m = \frac{c_s V_s}{A} \tag{6.3}$$

In equation (6.3), *m* represents the cake mass per unit membrane area,  $c_s$  is the feed water solids concentrations,  $V_s$  is the volume of the feed water and *A* represents the membrane surface area. This equation indicates that when the surface feed water characteristics changes due to higher or lower loading of solids concentrations, it would

influence the cake mass and ultimately affect the membrane filtration process. Under the constant flux filtration experiments, assumptions were made that throughout the 60 minutes filtration period the solids concentrations of the feed water samples remain the same by ensuring constant turbidity. By putting forward such assumption, it was anticipated that  $c_s$  was only required to be estimated once during the initial stage of every filtration sequence for feed water samples with constant turbidity.

It was mentioned earlier in this chapter that feed water turbidity analysis was much easier and faster to be conducted than its solids concentrations in the laboratories. Efforts have been made to establish a correlation between the feed water turbidity and its solids concentrations by using facilities commonly available in a typical water treatment plant in-house laboratory. Assumptions were made that these correlations remains valid within the experimental period of 3 months. Analyzing the current feed water sample turbidity would immediately provide an estimation of the solids concentrations or  $c_s$  to solve equation (6.3) and determine *m*. Both  $V_s$  and *A* were predetermined parameters in dead-end constant flux filtration operation mode.

Under normal circumstances, significant increase of TMP for constant flux filtration is a preliminary warning of potential membrane fouling propensity due to accumulation of solids on the membrane surface (Huang et al., 2014; Miller et al., 2014). Most industrial-scale UF membrane water treatment plants operating under dead-end constant flux filtration operation mode with surface feed water risked of having sudden high loading of suspended solids during heavy rain which might cause membrane fouling (Kim & DiGiano, 2009).

## 6.3.2.2 Using ANN model to predict specific cake resistance

An ANN predictive model was utilized to rapidly produce estimation of the specific cake resistance ( $\alpha$ ) for the first principle model. Literature has reported that values of  $\alpha$  require laborious experimental works to be determined and it changes very often in natural water sources (Ní Mhurchú & Foley, 2006). Utilization of the ANN predictive model allows tremendous savings in cost and efforts to estimate this parameter against the changing feed water characteristics. A typical industrial-scale UF membrane water treatment plant is lacked of the necessary equipment and skilled personnel to determine values of  $\alpha$  under the conventional analysis method in their in-house laboratory.

In this research, the estimation of  $\alpha$  was achieved by utilizing commonly available on-line data and simple laboratory analysis results as inputs data to the ANN predictive model. The utilization of ANN predictive model for estimation of membrane filtration performance has been reported to be capable of achieving acceptable accuracy (Choi et al., 2012). It has been reported in literature that feed water turbidity, TMP and filtration duration affects the potential membrane fouling propensity on dead-end UF processes (Villacorte et al., 2015). All these relevant parameters were fed as inputs to the ANN predictive model together with the immediate past value of the estimated specific cake resistance ( $\alpha_{r,l}$ ). This is known as dynamic ANN modelling to allow a much more accurate prediction of the outputs (Gautam & Soh, 2015). Even without any information concerning organic matter concentrations of the feed water, the ANN model was reported to be capable of predicting TMP of the UF system with high accuracy (Delgrange et al., 1998). Figure 6.2 shows the schematic of the ANN predictive model with the relevant inputs and output.



Hidden layer

Figure 6.2: Schematic diagram of the ANN predictive model

The hybrid model developed in this research was a combination of the ANN predictive model and the first principle/cake filtration model. Initially the ANN predictive model estimates the current value of the specific cake resistance ( $\alpha_t$ ) during the filtration process by using relevant inputs data including the immediate past value of the estimated specific cake resistance  $(\alpha_{t,l})$  as shown in Figure 6.2. Subsequently this parameter ( $\alpha$ ) was inserted into the cake filtration model to determine the feed water solids concentrations  $(c_s)$ . The combination of these 2 filtration parameters provides essential information on the potential membrane fouling propensity based on the operational conditions and feed water characteristics (Ju & Hong, 2014; Psoch & Schiewer, 2006). Literature has reported that both of these parameters are challenging to be precisely determined experimentally in the laboratories (Boerlage et al., 2004). This hybrid model provides an alternative method to estimate these two parameters without extensive laboratory analysis. It is essential to simplify the estimation methodology of these parameters for industrial-scale UF membrane water treatment plants due to facilities and resources constraint. Under the conventional analysis procedures, advanced analysis equipment or methods such as liquid chromatography-organic carbon detection (Chen et al., 2014), SEM (Reingruber et al., 2012), atomic scope microscope (Lee et al., 2001), ATR-FTIR (Marbelia et al., 2016), EDX (Zuo et al., 2014) or

fluorescence excitation-emission matrix spectroscopy (Peiris et al., 2013) are required to detect membrane fouling. Most of the industrial-scale UF membrane water treatment plants are not equipped with such sophisticated equipment and membrane samples are normally sent to third party laboratories for further analysis which could takes up a few weeks to evaluate the results. This hybrid model provides an alternative prediction/estimation method for the two parameters which allows a more rapid detection of potential membrane fouling conditions. These conditions could be due to the feed water characteristic changes or abnormal filtration operation of the water treatment plants.

## 6.3.2.3 Details of the hybrid model

In this research work, a hybrid model consisting of the ANN predictive model and the cake filtration model has been developed to allow rapid estimation of the two parameters ( $\alpha$  and  $c_s$ ) which lead to potential membrane fouling conditions. It was reported that feed water from natural sources were affected by many non-linear external factors which changes the water characteristics to a certain extent (Ní Mhurchú & Foley, 2006). In this hybrid modelling approach, commonly available data from the water treatment plants (feed water turbidity, filtration duration and TMP) were utilized as inputs for the parameters estimation. The simplicity of such approach allows a much easier integration into the water treatment plant monitoring procedures. This hybrid model was specifically targeted to predict the two parameters for UF systems operating under dead-end constant flux filtration mode which is the common operation mode for industrial-scale UF membrane water treatment plants.

In this hybrid model, the ANN predictive model was utilized to predict the specific cake resistance ( $\alpha$ ) during filtration. Assumption were made that the feed water

characteristics (particularly the solids concentrations of the samples) have negligible variations in a particular filtration sequence during the experiments. This was considered a valid assumption since most surface water sources would only have significant changes of turbidity after a few hours. Estimated values of  $\alpha$  shall be incorporated into the cake filtration model for the estimation of the feed water solids concentrations. The combination of these two models (ANN and cake filtration) enables rapid estimation of the parameters ( $\alpha$  and  $c_s$ ) which indicates the potential membrane fouling propensity. Such information allows the necessary precautions to be taken by the water treatment plant operators to mitigate the possibilities of membrane fouling.

#### 6.4 **Results and discussions**

Experiments have been conducted using facilities available at the UF membrane water treatment plant to determine the feed water characteristics (turbidity and solids concentrations) and membrane resistance ( $R_m$ ). Subsequently filtration experiments utilizing the pilot-scale UF system were carried out. All these results were organized for the ANN predictive model training and simulated using computer software. The simulated outputs were compared with the experimental results for verification and have been further elaborated in the following sections.

#### 6.4.1 Determination of membrane resistance, $R_m$

In order to determine the resistance for this particular UF hollow fibre membrane module, a graph of  $\Delta P_w$  against  $J_w$  was plotted and shown in Figure 6.3. In equation (6.1), when purified water (without any solids concentration) was used for the dead-end constant flux filtration,  $\alpha m = 0$ ,  $J = J_w$ ,  $\Delta P = \Delta P_w$  and  $R_m$  would be the slope of the

graph divided by  $\mu$  (water viscosity at room temperature) as indicated in equation (6.2). The data obtained from the filtration experiment using purified water shown in Figure 6.3 have indicated the membrane resistance ( $R_m$ ) as 1.77 X 10<sup>12</sup> m<sup>-1</sup>. Data provided by the UF membrane manufacturer indicated the membrane resistance of their product was 3.60 X 10<sup>11</sup> m<sup>-1</sup>. The discrepancy between the filtration experiment and the manufacturer's data occurs mainly because of two reasons. Possible main reason was because the manufacturer provided data of a single strand of the hollow fibre membrane resistance while experiments carried out in this work was done using an UF membrane module which consisted many strands of hollow fibre membrane packed into a module. The single strand hollow fibre membrane resistance was expected to be much lower because there was no effect of pressure losses due to hollow fibre networks compared to the UF membrane module which was packed with many strands of hollow fibre (Kostoglou & Karabelas, 2008). The second cause for the discrepancy was due to the hollow fibre geometrical arrangement inside the UF membrane module which causes various velocity and pressure fields that increase the pressure losses within the module (Cano et al., 2013). Most of the industrial-scale UF membrane water treatment plants including the earlier mentioned case studies were utilizing hollow fibre membrane in pressurized packed modules. It was more appropriate to determine  $R_m$  which incorporated the various pressure losses caused by the module geometry and the hollow fibre networks which were much higher than a single strand of hollow fibre membrane resistance. In this research work,  $R_m$  refers to the membrane resistance in the UF module which takes into considerations the additional resistance mentioned earlier. The same experimental procedures were repeated twice and the values of  $R_m$  obtained were between ±5% from all the experimental data. This indicates a good reproducibility of the experimental results.



Figure 6.3: UF membrane filtration data with purified water

#### 6.4.2 Filtration data with natural river water

The feed water to the pilot-scale UF system originates from the same river water source of the previous case studies on the industrial-scale UF membrane water treatment plant. Hollow fibre UF membrane utilized in the pilot-scale system was similar to the modified Polyethersulfone (mPES) produced by the same manufacturer of the UF membrane for the water treatment plant. In order to produce similar filtration condition, the filtration flux of the pilot-scale system was adjusted to 80 L/m<sup>2</sup>hr which was the same filtration flux applied on the industrial- scale system.

River water with turbidity of 96 NTU was collected (typically after a heavy rainfall) in a few large water containers with total volume about 3 m<sup>3</sup> of capacity. Samples water in these containers were allowed to settle between 1 to 12 hours and the top water layers from these containers were collected. Within the settling period, some suspended solids of the river water would have settled down at the bottom of the container producing less

turbid water on the top layer of the containers. River water samples with various turbidities of 52 NTU, 25 NTU and 12 NTU were collected for the experiments.

These river water samples (96 NTU, 52 NTU, 25 NTU and 12 NTU) were fed into the pilot-scale UF system in separate filtration sequences. All the experiments were conducted under dead-end constant flux filtration mode and the TMP (difference between the inlet port and filtrate port pressures) profile was recorded for 60 minutes period for each filtration sequences with different feed water samples. Figure 6.4 shows the results of the TMP profiles of all the feed water samples and purified water was utilized as the reference in this filtration test. All the feed water samples except for the purified water exhibited gradual increase of TMP within the 60 minutes filtration duration. These results were expected as there were various degrees of suspended solids concentrations in each feed water samples which had accumulated on the membrane surface and increased the filtration resistance. Filtration sequence of the sample with the highest turbidity (96 NTU) indicated the fastest increase of TMP primarily because of the higher concentration of suspended solids in the sample.



Figure 6.4: Filtration TMP profiles of feed water samples

It was reported in literature that a correlation between log of turbidity and filtration flux of some natural surface water could be established (Shengji et al., 2008). Although it might be applied in some locations, the mathematical correlation might differ for some other sources. The feed water samples obtained in this study have very little variation of pH which normally falls between 6.5 and 7.5 and assumptions were made that the pH values of the water samples do not have significant effect on the filtration mechanism.

## 6.4.3 Analysis to establish correlation of the feed water parameters

A correlation between the feed water turbidity and its solids concentrations was established with laboratory analysis. It has been reported that a simple correlation between turbidity and solids concentrations of natural surface water could be determined experimentally (Solak et al., 2009; Yahyapour et al., 2014). A detailed study of the River Neckar in Germany conducted by other researchers haven shown the ratio of solids concentrations/turbidity was between  $1.5 - 1.9 \text{ mgL}^{-1}\text{NTU}^{-1}$  (Rügner et al., 2014). The analysis of many feed water samples from the river source to the UF membrane water treatment plant collected during the year 2015 were shown in Figure

6.5.



Figure 6.5: Analysis results of river water solids concentrations against turbidity

The results in Figure 6.5 indicated an almost linear correlation between river water total suspended solids (TSS) concentrations and its turbidity. Ratio of the TSS concentrations/turbidity from Figure 6.5 indicated 1.6 mgL<sup>-1</sup>NTU<sup>-1</sup> which falls within the range of 1.5 - 1.9 mgL<sup>-1</sup>NTU<sup>-1</sup> reported in literature (Rügner et al., 2014). Such TSS concentrations/turbidity correlation might differ from time to time when the river water characteristics changes due to natural causes or man-made activities. It is necessary to update the data from recent laboratory analysis results to re-establish the correlation to ensure its accuracy (Rügner et al., 2014). The correlation of the data obtained through analysis could be further utilized to derive the cake mass per unit membrane area (*m*) indicated in equation (6.3). Analysis of the feed water turbidity allows the solids concentrations of the feed water (*c<sub>s</sub>*) to be estimated from the correlation established in Figure 6.5. Since all the experiments were conducted under dead-end constant flux filtration mode both *V<sub>s</sub>* and *A* could be derived by knowing the total membrane surface area in the module (6 m<sup>2</sup>) and the filtration flux (80 L/m<sup>2</sup>hr).

# 6.4.4 Estimation of specific cake resistance with Darcy's law

All the relevant data in Figure 6.5 were utilized for the estimation of m using Subsequently the data of  $\alpha$  was determined with Darcy's law in equation (6.3). equation (6.1) as shown in Figure 6.6. It was mentioned earlier that  $\alpha$  is dependence on the feed water characteristics besides turbidity which complicates the experimental analysis of this parameter. In this research, data of  $\alpha$  from the ANN predictive model enables rapid estimation of this parameter with simple laboratory analysis. Only feed water solids concentration and its turbidity analyses were required to establish the TSS concentrations/turbidity correlation. When significant feed water а TSS concentrations/turbidity correlation changes was observed, more recent data might be required to re-train the ANN predictive model.



Figure 6.6: Estimated specific cake resistance based on Darcy's law

## 6.4.5 Development of the ANN predictive model

Development of the ANN predictive model was accomplished using mathematical software called MATLAB. It was also utilized to simulate the ANN predictive model outputs with the related inputs. The whole ANN architecture and related information regarding the network has been shown in Table 6.2.

Parameters	Hidden layer	Output layer	
Activation function	Tansig	Linear	
Number of nodes	5 nodes	1 node	
Mean squared error (MSE)		9.87 X 10 <sup>-4</sup>	
Networks training method	Levenberg-Marquardt backpropagation		

Table 6.2: ANN predictive model architecture

The relevant inputs and outputs data depicted in Figure 6.2 were fed into the ANN predictive model for the training. A single hidden layered feed-forward back-propagation ANN structure was used for the training. It was reported in literature that the required number of nodes in the hidden layer should be determined heuristically (Ganguly et al., 2016). The mean squared errors (MSE) against the number of hidden nodes were shown in Figure 6.7. In this figure it was indicated that the minimum MSE for training was achieved when the number of hidden nodes was 5. This ANN architecture applied was one of the most conventional and there were other various advanced ANN training methods for more complicated systems or processes (Zhang & Suganthan, 2016). These advanced or multiple layered ANN models were intended to be utilized for more complex systems such as voice recognition (Li et al., 2013; Pawlus et al., 2013) which might not be suitable for simple systems. In this research works, 4

sets of TMP profiles with various feed water turbidity (96 NTU, 52 NTU, 25 NTU and 12 NTU) were utilized for the ANN training. The quality and relevance of the training data was much more important than the quantity of the data. A total of 52 data points were used and all of the data have been selected based on the relevant impact to the desired outputs. This is because the ANN estimated output accuracy is strongly related to the data used during the training process (Sun et al., 2014). The training data covers the most possible operation conditions of the UF system under this research. Figure 6.7 indicates the MSE of using 5 hidden nodes was 9.87 X  $10^{-4}$  which was the lowest among all the tested number of hidden nodes. Parity plots results indicated the coefficient of determination or  $\mathbb{R}^2$  values of above 0.90 between the actual and predicted data by the ANN predictive model in both the training and validation data sets.



Figure 6.7: MSE of various numbers of hidden nodes during ANN training

Under normal circumstances, the industrial-scale UF membrane water treatment plant in the case studies mentioned earlier should be treating feed water with turbidity of 20 NTU or below as per the design requirements. Unfortunately during heavy rainfalls, the feed water could sometimes abruptly exceed this turbidity limit but nevertheless most of the daily average feed water turbidity was only between 10 - 15 NTU. In this research, emphasis was made to cover the most probable and common range of feed water turbidity which was between 10 - 20 NTU. Figure 6.8 shows the simulated results against the experimental analysis for feed water samples of 10 NTU and 20 NTU respectively. The ANN predictive model results were simulated using computer software while the experimental results were obtained using the pilot-scale UF system shown in Figure 6.1.



Figure 6.8: Simulation and experimental results of the specific cake resistance

Simulation results indicated in Figure 6.8 displayed close agreement against the laboratory experimental analysis. Initially the values of  $\alpha$  were decreasing (the first 20 minutes) and subsequently stabilized into constant values against filtration duration. When feed water samples consisting of the suspended solids were introduced onto the

membrane surface, a solids cake layer starts to form. After certain duration the values of  $\alpha$  gradually stabilized or in a stage known as cake consolidation which very little changes of  $\alpha$  was noticed. Further filtration or accumulation of solids after the cake consolidation stage would increases the values of  $\alpha$  which have been reported in literature (Sioutopoulos & Karabelas, 2016). Significant increase of  $\alpha$  after the cake consolidation stage is a less desirable condition as the potential membrane fouling propensity would also increases.

## 6.4.6 Validating the hybrid model with experimental results

Estimated values of  $\alpha$  obtained through computer software simulation of the ANN predictive model shown in Figure 6.8 was fed into the first principle/cake filtration model to determine the average values of the feed water solids concentrations ( $c_s$ ). The results have been tabulated in Table 6.3.

Time	Actua	al TMP	Simulated, $\alpha$		Simulated, $c_s$	
(min)	(kPa)		(X 10 <sup>15</sup> m/kg)		$(kg/m^3)$	
	10 NTU	20 NTU	10 NTU	20 NTU	10 NTU	20 NTU
5	40	41	1.44	1.30	0.026	0.029
10	42	42	1.10	0.83	0.017	0.027
15	43	42	0.95	0.59	0.019	0.030
20	45	43	0.86	0.46	0.018	0.029
25	47	46	0.81	0.40	0.019	0.030
30	48	48	0.79	0.38	0.019	0.036
35	49	50	0.78	0.38	0.018	0.037
40	51	52	0.78	0.38	0.017	0.037
45	53	54	0.77	0.39	0.017	0.037
50	54	55	0.77	0.44	0.018	0.033
55	56	56	0.77	0.46	0.017	0.030
60	57	57	0.78	0.48	0.017	0.029
Average simulated results				0.019	0.032	
Laboratory analysis results					0.018	0.031

Table 6.3: Hybrid model simulation and laboratory analysis results
Data shown in Table 6.3 have indicated that the average simulated results of the solids concentrations ( $c_s$ ) of both the feed water samples (10 NTU and 20 NTU) were close matches to the laboratory analysis results obtained from the feed water. Further validation of the model were conducted by comparing the data of TMP from computer software simulation of the ANN predictive model against the actual TMP results obtained through the UF pilot-scale system shown in Figure 6.9. The results again indicated close agreement between the simulated and the experimental results. This shows that the feed water characteristics particularly the TSS concentrations/turbidity correlation depicted in Figure 6.5 was still valid. It was suggested that once there were significance differences between the simulated and actual TMP, the feed water characteristics might have changed and subsequently more recent analysis data would be required to re-establish the TSS concentrations/turbidity correlation. Similarly the ANN predictive model would also be required for re-training with more updated data.



Figure 6.9: Simulation and experimental results of the TMP

In order to further examine the validity of this hybrid model on other system, data of suspended solids concentrations of feed solutions ( $c_{s,data}$ ), TMP ( $TMP_{data}$ ) and its specific cake resistance ( $\alpha_{data}$ ) from literature (Sripui et al., 2011) were fed into the hybrid model. These data were obtained from rice wine suspension filtered through microfiltration membrane under dead-end operation. Table 6.4 indicates the literature data ( $\alpha_{data}$ ,  $c_{s,data}$  and  $TMP_{data}$ ) and the calculated membrane resistance ( $R_{m,cal}$ ) obtained by using the hybrid model.

$\alpha_{data}$ (m/kg)	$c_{s,data}$ (kg/m <sup>3</sup> )	TMP <sub>data</sub> (kPa)	$R_{m,cal} (\mathrm{m}^{-1})$
50 X 10 <sup>10</sup>	2.0	$1.52 \times 10^3$	7.7 X 10 <sup>13</sup>
45 X 10 <sup>10</sup>	1.0	$1.36 \times 10^3$	6.9 X 10 <sup>13</sup>
40 X 10 <sup>10</sup>	0.5	$1.21 \times 10^3$	6.1 X 10 <sup>13</sup>

Table 6.4: Calculated values of membrane resistance  $(R_{m,cal})$  and data from literature

Data from Table 6.4 shows  $R_{m,cal}$  as the calculated values of the microfiltration membrane resistance using equation (6.1) and (6.3) from the hybrid model. These calculated  $R_{m,data}$  indicated almost a consistent value of 6.9 X 10<sup>13</sup> m<sup>-1</sup> ± 12% which is in accordance to Darcy's law.

#### 6.4.7 Sensitivity analysis of the hybrid model

The main purpose of conducting sensitivity analysis is to compare different inputs or parameters on a specific process model for evaluation (Amidpour et al., 2015). Even though all the inputs/parameters to the ANN predictive model were necessary and important, some have higher weightages than others on the estimated outputs. The variations of these inputs/parameters were plotted against the ANN outputs ( $\alpha$ ) to determine any relevant or observable patterns. Three inputs/parameters selected for the sensitivity analyses were feed water solids concentrations ( $c_s$ ), TMP during filtration sequence and feed water turbidity. In the sensitivity analysis, only one input/parameter was varied while the other inputs/parameters remain. Figure 6.10 shows the sensitivity analyses results of various inputs/parameters against the outputs of the ANN predictive model ( $\alpha$ ).



Figure 6.10 (c)  $\alpha$  against feed water turbidity (end of filtration)



Figure 6.10 (c) indicated that there was a strong correlation between feed water turbidity and ultimate values of  $\alpha$  at the end of the filtration sequences for the samples. This might be caused by the fact that all the feed water samples were obtained from the same river source at similar time with the only major differences in turbidity and solids concentrations. It was suggested that the main parameters which affects  $\alpha$  such as particle shape, particle size distribution, porosity and density of the suspended solids (Sripui et al., 2011) in the feed water samples were of same characteristics. Literature has reported similar linear correlation in membrane filtration for  $\alpha$  and solids concentrations of the feed solutions (Sripui et al., 2011). Therefore it was essential to ensure the TSS concentrations/turbidity correlation remains relevant to the current filtration process and feed water characteristics. It has been suggested in literature that the product of  $\alpha c_s$  is also known as fouling index which was commonly utilized to indicate potential membrane fouling propensity (Boerlage et al., 2004; Boerlage et al., 2003; Boerlage et al., 2000; Boerlage et al., 1998).

Another parameter which exhibited some degree of correlation with  $\alpha$  was the TMP during filtration shown in Figure 6.10 (b). The values of  $\alpha$  decrease against TMP during initial filtration and ultimately stabilized to almost a constant value at the end. Finally the values of  $c_s$  and  $\alpha$  during filtration exhibited the most minimal correlation shown in Figure 6.10 (a). This has also been reported in literature whereby it was found that  $\alpha$  was primarily affected by particle size distribution and particle shape which were not only subjected to the solids concentrations alone (Bourcier et al., 2016).

## 6.5 Applying the hybrid model in UF membrane water treatment plant

As mentioned earlier in this chapter, the main purpose of the hybrid model development was to allow rapid estimation of the parameters associated with potential membrane fouling propensity for UF system operating under dead-end constant flux filtration mode. This estimation method is required to be aligned with the commonly available facilities in a typical industrial-scale UF membrane water treatment plant. These facilities include laboratory turbidity analyzer, on-line pressure transmitters (to record TMP), digital timer (to record filtration duration) and other simple laboratory equipment to analyze feed water solids concentrations. The two estimated parameters ( $\alpha$ and  $c_s$ ) from this hybrid model were reported to have a direct impact on the potential membrane fouling propensity (Ju & Hong, 2014). Validation of this hybrid model could be further substantiated on an industrial-scale UF membrane water treatment plant with much higher membrane surface area than the pilot-scale system. In this research, the feed water samples originates from the same river water source to the industrial-scale UF membrane water treatment plant described earlier in the case studies. Results obtained in this research works with the pilot-scale UF system paves the way for a much more extensive plant-trial of the hybrid model for future studies.

One of the most significant differences between this hybrid model and other conventional models (Lee et al., 2001; Mahdi & Holdich, 2013; Zhou et al., 2015) is the simplified method of parameters estimation with commonly available facilities in water treatment plants. It eliminates the use of advanced analysis equipment which is seldom available at the in-house laboratories of typical water treatment plants. It was reported that utilization of hybrid models are complementary modelling methods leveraging on both the advantages of theoretical and black-box models. (Meroney, 2016; Xiaoyi et al., 2016). The hybrid model developed in this research combined both the first principle/cake filtration model (theoretical) and the ANN predictive model (black-box)

to yield a more comprehensive and rapid estimation method of the two filtration parameters ( $\alpha$  and  $c_s$ ).

It was also reported in literature that a properly trained conventional feed-forward ANN model could provide better accuracy than regression model (Chithra et al., 2016; Ghosh et al., 2016). It has been assumed that this hybrid model accuracy was not as high as other theoretical models reported in literature (Carbonell-Alcaina et al., 2016; Kostoglou & Karabelas, 2016; Vinther & Jönsson, 2016) but nevertheless this hybrid model provides an early warning of potential membrane fouling conditions. It is intended to be implemented on industrial-scale UF membrane water treatment plant with its existing facilities as part of their monitoring procedures.

One of the main challenges of this hybrid model is the characteristic changes of the natural river water source. It is important to ensure the TSS concentrations/turbidity correlation is updated regularly to reflect the latest feed water characteristics. It is not practical to analyze the feed water solids concentrations a few times a day as it involves lots of effort and very time consuming (Pavanelli & Bigi, 2005). A weekly updated database of the feed water TSS concentrations/turbidity correlation is highly recommended to facilitate the efficient implementation of the hybrid model. Any significant changes of feed water characteristics could then be observed and re-training of the ANN predictive model should be conducted if necessary.

There were certain limitations of this hybrid model which require further attentions. Firstly, any irreversible fouling of the UF membrane was not taken into consideration in this hybrid model. Moderate irreversible membrane fouling causes much higher increase of the on-line TMP during filtration which might be significantly different than the simulated TMP profile from the hybrid model. The discrepancy of the TMP profiles (simulated and on-line) served as an indication that new data gathering is required to retrain the ANN model again. It was assumed that after each filtration sequence, a hydraulic backwash sequence would clean or dislodge all foulant from the membrane surface. Under actual operational conditions, an irreversible fouling layer would be formed after prolong period of continuous operation usually within a few months. It is a complicated process to predict the rate of membrane fouling due to various different operating conditions of the system (Liu et al., 2009). This hybrid model provides an estimation tools to present information of any potential membrane fouling conditions. It was suggested that ANN models could also be utilized as process controller to mitigate the membrane fouling process by allowing more efficient filtration and backwash sequences which have been reported in literature (Li & Li, 2016; Moon & Jung, 2016).

It should be emphasized that the hybrid model developed in this research was intended as an alternative method of estimating  $\alpha$  and  $c_s$ . Fundamental theoretical models was scientifically proven with much higher accuracy to represent the filtration process. Nevertheless to accommodate the requirements and limited resources available in an industrial-scale UF membrane water treatment plant, the hybrid model might be a useful tool for early detection of potential membrane fouling conditions. Table 6.5 highlighted the comparisons of the hybrid model developed in this research against the conventional/theoretical filtration model.

	Theoretical filtration modelling	Hybrid modelling
Analysis equipment	Often requires advanced analysis equipment and methods such as liquid chromatography-organic carbon detection, SEM, atomic scope microscope, ATR-FTIR, EDX and fluorescence excitation- emission matrix spectroscopy. (Chen et al., 2014; Lee et al., 2001; Marbelia et al., 2016; Peiris et al., 2013; Reingruber et al., 2012; Zuo et al., 2014).	Utilizes simple laboratory analysis and commonly available data from an industrial-scale UF membrane water treatment plant.
Feed water characteristics	Simulated feed solution of known solids concentrations were commonly used to ensure controlled conditions (Sioutopoulos & Karabelas, 2012; Tian et al., 2013b; Yi et al., 2013).	Natural surface water with changing characteristics (especially turbidity and solids concentrations).
Modelling approach	Fundamental theoretical or white- box model with high precision and accuracy to the actual process (Lee et al., 2001; Mahdi & Holdich, 2013; Zhou et al., 2015).	Combination of both theoretical/white-box model and black-box model with acceptable accuracy
Duration of analysis	Require extensive effort and time consuming analysis (Boerlage et al., 2004)	Estimations were obtained almost instantaneously with simulation software fed with on-line data
Cost impact	High cost impact due to requirement of advanced equipment and skilled personnel for analysis (Pavanelli & Bigi, 2005)	Low cost impact which entails the upgrading of the monitoring software with the hybrid model

## Table 6.5: Comparisons between theoretical filtration and hybrid models

# 6.6 Summary

In this research, a practical hybrid model has been developed for the dead-end constant flux filtration mode of the UF process. This mode of operation is commonly implemented on industrial-scale UF membrane water treatment plants. The hybrid model consists of a theoretical cake filtration model and an ANN predictive model implemented to estimate two potential membrane fouling parameters. The two parameters predicted in this research were feed water solids concentration  $(c_s)$  and specific cake resistance ( $\alpha$ ). Experimental data from the UF pilot-scale system and laboratory analysis of the feed water characteristics were utilized to train and validate the ANN predictive model. Simulation results of the hybrid model have indicated close agreement with the experimental results for feed water samples of 10 NTU and 20 NTU respectively. The two parameters estimated from this hybrid model provides early warning of potential membrane fouling conditions due to changes of feed water characteristics. Significant differences between the simulated TMP from the hybrid model and the actual on-line TMP during filtration would indicate changes of the feed water characteristics which require further attention. The hybrid model could be retrained with more updated data of the feed water characteristics for more accurate prediction of the parameters. Sensitivity analysis conducted on the hybrid model shows a strong correlation between feed water turbidity and the ultimate values of  $\alpha$ . This hybrid modelling approach is an alternative method to detect potential membrane fouling conditions in UF membrane water treatment systems. The hybrid model utilized commonly available on-line data and simple laboratory analysis for the estimation of the two parameters without requiring advanced analysis facilities which are commonly not available at the in-house laboratories of water treatment plants.

#### **CHAPTER 7:**

# ARTIFICIAL NEURAL NETWORKS CONTROL FOR ULTRAFILTRATION MEMBRANE WATER TREATMENT SYSTEM

Ensuring efficient operation of the ultrafiltration membrane water treatment system through process control is an essential design. The dead-end membrane filtration process consists of two important sequences known as filtration and backwash. Implementing efficient process control on both sequences alleviate the potential membrane fouling propensity while ensuring the required productivities are achieved. An efficient control system also leads to the reduction of water losses through intermittent backwash of the dead-end membrane filtration process. Although the conventional set-points control is widely implemented in the industrial-scale UF membrane water treatment plant automation system, it has its limitations. An alternative process control system utilizing ANN model and controllers has the potential to overcome such limitations.

## 7.1 Introduction

Fluctuations of the natural feed water characteristics pose huge challenges to the operation of industrial-scale UF membrane water treatment plants. In order to ensure continuous automated operation, the conventional set-points control system is often applied on the maximum limits of TMP, filtration and backwash durations of the deadend membrane filtration process. In this chapter, an alternative process control system utilizing ANN model and controllers has been developed and implemented on-line with an UF experimental system. This alternative process control has been utilized on the dead-end constant flux UF membrane system to ensure reduction of water losses within acceptable potential membrane fouling propensity of the system.

## 7.2 Background

Rapid industrial development and continuous increase of human population has caused enormous consumption of clean water supply especially in high density urban areas (Goh et al., 2016). In order to fulfill the ever increasing demand for clean water supply, countries in the Middle East region have constructed many industrial-scale membrane water treatment plants to satisfy their nation's needs (Amy et al., 2017). The advantages and sustainability of membrane systems are exhibited through their adaptability, flexibility, lower environmental impacts and minimal foot print necessity (Le & Nunes, 2016). UF membrane systems are capable of producing consistent filtrate quality which is free from particles, bacteria and viruses to achieve potable/drinking water standards (Monnot et al., 2016). Most industrial-scale UF membrane water treatment plants are operating under dead-end filtration mode with constant flux rate. This operation mode consists of filtration and intermittent backwash sequences to significantly reduces energy utilization compared to cross-flow filtration operation mode (Massé et al., 2011). Majority of the UF membrane water treatment plants utilize polymeric membranes such as Polivinylidene fluoride (PVDF) or Polyethersulfone (PES) due to their lower cost of production and acceptable quality (Hög et al., 2015). Additives could be added in PES membrane to modify or enhance its hydrophilicity and reduces membrane fouling issues (Vatsha et al., 2014).

One of the most critical and common problems with membrane systems are the fouling issues (Guo et al., 2012). Efforts to mitigate membrane fouling include various recommended methods such as physical membrane cleaning, membrane surface

modification and hydrodynamic flushing to dislodge and remove attached solids/foulant on the membrane surface and pores (Shamsuddin et al., 2015). The main purpose of membrane cleaning is to establish a set of procedures to dislodge non-integral substances or solids known as foulant from the membrane (Porcelli & Judd, 2010). Hydraulic backwash is a common physical membrane cleaning method applied to mitigate or reduce the irreversible fouling of membrane (Chang et al., 2015). Under the dead-end filtration mode, after each filtration sequence an intermittent backwash is initiated as physical membrane cleaning to recover the membrane permeability before the next filtration sequence commences (Mendret et al., 2009). Preventive procedures such as optimization of the membrane systems operational condition could mitigate and reduce possibilities of irreversible membrane fouling (Shi et al., 2014). During the filtration sequence, foulant or solids are accumulated on the membrane side where the feed water is pressurized. A layer of solids/foulant known as cake would be formed and increases the resistance of the liquid moving across the membrane. After a specific duration, the filtration sequence ceases and clean water is introduced from reverse direction of the UF membrane in the backwash sequence. It is a common practice to use higher flux rate during backwash to exert the required hydraulic force and dislodge the foulant. The pore size of the UF membrane segregates the larger solid particles, bacteria and viruses from contaminating the filtrate under the cake filtration model. During backwash, this cake layer is hydraulically pressurized from the reverse side of the membrane with clean water to remove these foulant from the membrane. Figure 7.1 illustrate the filtration and backwash sequences of a typical dead-end UF process.



Figure 7.1: Filtration and backwash sequences for dead-end UF process

Common feed water sources to industrial-scale water treatment plants originate from natural surface water which is deemed suitable for the treatment processes (Davies & Mazumder, 2003). These natural water sources contain a variety of organic matters which constitute major foulant on the UF membranes that reduces its permeability (Shang et al., 2015). The two most important components which requires attention in UF systems are operational condition and feed water characteristics (Decarolis et al., 2001). It was reported in literature that any composition or characteristic changes of the feed water would causes significant impact on the membrane fouling potential (Massé et al., 2015). Under normal circumstances, industrial-scale water treatment plant operators would monitor and analyze the feed water turbidity and pH periodically or on-line to determine possibilities of feed water characteristics fluctuations. In the membrane filtration process, specific cake resistance or  $\alpha$  is considered an important parameter for

estimation of potential membrane fouling propensity (Sioutopoulos & Karabelas, 2016). This parameter is generally not measured or analyzed in the industrial-scale UF membrane water treatment plant's own in-house laboratory due to the lack of equipment and skilled personnel.

The Darcy's equation or model is commonly utilized to represent the resistance caused by the formation of foulant cake layer in the dead-end filtration mode (Sioutopoulos & Karabelas, 2015). In this theoretical model, specific cake resistance during filtration and the solids concentrations of the feed solutions are taken into considerations. Any significant characteristics changes of the feed water would have noticeable impact on the filtration process. Natural surface water which is the main source of feed water to industrial-scale UF systems is known to have fluctuating characteristics due to weather conditions and man-made activities. Industrial-scale UF membrane water treatment plants operating under dead-end constant flux filtration mode encounter issues such as increasing TMP during filtration due to accumulation of solids/foulant as cake layer which originates from the feed water (Iritani et al., 2015). The increased of feed water pressure to maintain constant flux is undesirable as more energy is utilized to produce the same amount of filtrate.

Industrial-scale UF membrane water treatment plants operating under the dead-end constant flux filtration mode commonly implements the conventional set-points control system. This system pre-determined the filtration timer and maximum allowable TMP set-points in the filtration sequence as well as a backwash timer in the backwash sequence (Cogan & Chellam, 2014). The conventional set-points control is programmed into programmable logic controllers (PLC) to execute the automation of the processes (Alphonsus & Abdullah, 2016). Common hardware involved in the UF processes are control valves, pumps and pressure transmitters. Figure 7.2 shows the typical schematic diagram of the conventional set-points control for the UF process in dead-end operation

mode. The parameters X, Y and Z in Figure 7.2 are the pre-determined set-points to trigger the next sequence.



Figure 7.2: Schematic diagram of the conventional set-points control system

Fluctuations of the feed water characteristics, turbidity and solids concentrations are some of the major issues in the operation of industrial-scale UF water treatment plants. It is common that such unexpected changes of the feed water are the major causes of membrane fouling and water wastages because the control systems were not adjusted accordingly. Process control is one of the main components of membrane systems to enhance its efficiency (Damour et al., 2014). Unforeseen characteristics changes of the feed water further complicates the complex interaction between the membrane and foulant which prevents the use of theoretical model to represent membrane fouling processes (Shetty & Chellam, 2003). Under such undesirable conditions, ANN could be utilized as an alternative black-box model to represent these processes (Shetty et al., 2003).

Reduction of water losses and mitigation of membrane fouling are essential process control for membrane filtration to ensure sustainability of the systems. Under the conventional control of dead-end membrane filtration operation mode, a fixed duration of intermittent backwash at specific flowrate is introduced at the end of each filtration sequence (Remize et al., 2010). Literature has reported the utilization of Aluminiumbased coagulant as a significantly effective control procedure to enhance coagulation of organic matters and reduces UF membrane fouling (Yan et al., 2017). Utilization of coagulation and pulsed short-wavelength ultraviolet light is another advanced method to reduce micro-organism from fouling the membrane (Yu et al., 2016). Theoretical optimized dosing of coagulant in membrane system was also used to control membrane fouling (Gao et al., 2017). Under this approach, an on-line self-adaptive cycle-to-cycle coagulant dosing control system has been found to be very robust in performing the task. The main components of all these highlighted methods mentioned earlier require the control of coagulant dosage or advanced equipment utilization which incurred significant cost. Direct feed UF membrane water treatment plants do not require any coagulant to produce potable/drinking water from low turbidity natural surface water with substantially lower operational cost. The utilization of common laboratory analysis and on-line data for process control of such treatment plants to minimize water losses and mitigate membrane fouling are seldom reported in literature. In this work, an ANN control system has been developed and compared with the efficiency of a conventional set-points control system to reduce water losses for the direct feed UF membrane water treatment system.

## 7.3 Methodology

An UF membrane experimental system was designed to implement real-time process control and monitoring under dead-end constant flux filtration mode. UF membrane module model Dizzer P 2521-1.0 manufactured by Inge GmbH, Germany was utilized in this system. The UF membrane module consists of 1.0 m<sup>2</sup> of hollow fibre membrane surface area made from modified PES (mPES) material. This UF experimental system was utilized to obtain the necessary filtration data such as TMP profiles, filtration and backwash durations. Figure 7.3 shows the actual UF experimental system completes with the supervisory control and data acquisition (SCADA) software linked to a laptop computer.



Figure 7.3: UF experimental system equipped with laptop computer control

The UF experimental system was equipped with pressure transmitters to record the TMP profiles in real-time during operation. Another important component of the system was the final control elements which consist of four units of control valves and two units of pumps (feed pump and backwash pump). Two tanks were connected to the UF experimental system to store the feed water and filtrate. All the relevant on-line data recording and control were executed from a laptop computer installed with the necessary SCADA software. Figure 7.4 shows the process and instrumentation diagram (P&ID) of the UF experimental system.



Figure 7.4: Process and instrumentation diagram (P&ID) of the UF experimental system

A control panel was connected to the laptop computer to operate the SCADA system. The SCADA system utilized mathematical simulation software known as MATLAB as the graphical user's interface (GUI) for the system to implement real-time monitoring and control. This UF experimental system operational conditions have been designed to mimic the industrial-scale UF membrane water treatment system mentioned earlier in the case studies in Chapter 3, 4 and 5 at a much smaller scale. The TMP, filtration and backwash durations were recorded digitally in the SCADA system. Flow rates during filtration or backwash and feed water turbidity were measured/analyzed manually. All of these parameters (filtration flow rate, backwash flow rate and feed water turbidity) were entered into the SCADA system during the initial stage and assumed to remain constant during the whole operation.

On-line data was recorded under an open loop system with constant feed water turbidity and filtration flux rate. The TMP profile and filtration durations were recorded for further development of the ANN model and controllers. Figure 7.5 shows the block diagram of the ANN control system architecture in this research.



Figure 7.5: Block diagram of ANN control system architecture

The operation of this UF experimental system was controlled using the SCADA software as the GUI. There were 6 control elements (4 control valves and 2 pumps) and 2 input sensors (pressure transmitters located at the inlet and filtrate ports of the UF module) connected to the SCADA system. During operation, all the outputs and inputs

data from the filtration and backwash sequences were recorded into the SCADA software. This UF experimental system allows both the conventional set-points and ANN control systems to be implemented on-line. The GUI of MATLAB is shown in Figure 7.6. All the relevant information of the operation including the real-time TMP profiles were displayed from the computer's screen and the data was digitally recorded for further analysis. The following sections further elaborate on the development and implementation of these control systems.



Figure 7.6: Graphical user's interface of the SCADA system

#### 7.3.1 Implementation of conventional set-points control system

As mentioned earlier, the conventional set-points control system is commonly implemented in the industrial-scale UF membrane water treatment plants. Set-points are pre-determined for both the filtration and backwash sequences of the dead-end filtration mode process. During the filtration sequence, a filtration duration set-point is normally pre-determined (typically between 20 - 60 minutes) to produce the desired volume of filtrate. As a precaution, a maximum TMP set-point (typically above 2.0 Bar) is also introduced to avoid abnormally high pressure on the UF membrane module. Under normal circumstances the set-point of the filtration duration would be triggered first to cease the filtration sequence before reaching the maximum TMP set-point. After completing the filtration sequence, the backwash sequence ensues to provide hydraulic cleaning of the membrane which is typically between 30 to 120 seconds. The filtration and backwash sequences operate on alternate basis and the cycle continues until a chemical cleaning of the membrane is required after completion of 24 continuous cycles as mentioned earlier in Chapter 3. Under this research, emphasis was laid to control the duration of both filtration and backwash sequences before reaching the maximum setpoint of the filtration TMP. All the experiments were conducted using the same river water source as the industrial-scale UF membrane water treatment plant mentioned earlier in the previous case studies. The same set-points implemented on this industrialscale UF membrane water treatment plant were used in the UF experimental system to mimic the operation of the treatment plant.

#### 7.3.2 Development and implementation of ANN control system

Before developing the ANN control system, actual filtration data was required for the training of the model and controllers. The TMP profiles data were gathered using the UF experimental system while the feed water turbidity and solids concentrations analyses were conducted using facilities available at the in-house laboratory of the industrial-scale UF membrane water treatment plant. Various feed water samples were

collected from the river source to represent turbidity of 5 NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU. These various feed water samples were obtained by collecting a large volume of river water when the river water turbidity was about 30 NTU to 40 NTU in a water storage tank. Subsequently the river water in the storage tank was allowed to settle between 1 to 12 hours and the top water layer in the tank was scooped out to represents the 5 different turbidity readings. The five samples of river water were fed into the UF experimental system under dead-end constant flux filtration mode to obtain the TMP profiles for 60 minutes of filtration duration. Constant flux or flow rate in this research is defined as  $\pm 10\%$  of the desired filtration flux/flow rate. Typically during the initial commencement of the filtration sequence the flow rate was set at 10% higher than the desired flowrate. As the TMP increases during filtration sequence, the flow rate would be reduced to within the  $\pm 10\%$  tolerance at the end of the sequence. The same set of procedures was applied on the backwash sequence as well. Development of the ANN control system consists of two major components which are:-

- 1. One ANN predictive model to estimate values of  $\alpha$  during filtration.
- 2. Two ANN controllers to control the backwash and filtration durations respectively.

Data were collected using the UF experimental system to train and validate the ANN model and controllers. The details on the development of these two major components have been further highlighted in the following sections.

### 7.3.2.1 ANN predictive model for estimation of specific cake resistance

The detailed development of the ANN predictive model for parameters estimation in the dead-end filtration process was highlighted in Chapter 6. Potential membrane fouling propensity represented by the product of  $\alpha c_s$  is a main concern to ensure minimal risk of the UF membrane fouling (Boerlage et al., 2000). Utilizing analysis data of the feed water turbidity and on-line data (TMP profiles and filtration time), the ANN predictive model continuously estimates the values of  $\alpha$  during the filtration sequence. In order to establish the correlation between feed water turbidity and its solids concentrations, similar analysis and experimental procedures described in Chapter 6 was applied. The ANN predictive model provides an alternative rapid estimation method for values of  $\alpha$  which are very time consuming to determine under the conventional laboratory analysis method. This alternative estimation method is suitable to be implemented on industrial-scale UF membrane water treatment plants which have limited laboratory resources and skilled staff to analyze it using the conventional method. Details development of the predictive ANN model has been further elaborated in Chapter 6.

#### 7.3.2.2 Development of ANN controllers for filtration and backwash sequences

After obtaining the estimated values of  $\alpha$  with the predictive model, the ANN control system utilized this parameter as one of the inputs to decide the filtration duration. There are two ANN controllers involved which are known as:-

- 1. ANN controller number 1 determine filtration duration
- 2. ANN controller number 2 determine backwash duration

ANN controller number 1 controls the filtration duration and the ANN controller number 2 controls the backwash duration. Before commencing the filtration sequence, the turbidity of the feed water sample was analyzed and the value was entered as part of the ANN controller number 1 inputs. The turbidity of the feed water was assumed to be constant throughout the whole filtration sequence so the data of the turbidity was only entered once into the SCADA system. Other inputs data such as on-line TMP ( $TMP_{ol}$ ), cake mass per unit membrane area (m) and the estimated  $\alpha$  from the ANN predictive model were also fed into the ANN controller number 1.

Initially when the filtration sequence commences, the data of the feed water turbidity was utilized to estimate the duration of data collection. During this data collection period the controller would allow the filtration sequence to continue without any interruptions. This is to allow sufficient on-line TMP ( $TMP_{ol}$ ), m and  $\alpha$  data to be gathered for the ANN controller number 1 to make an accurate estimation of the filtration duration or  $T_{fil}$ . On-line data of all the inputs were recorded every second in the SCADA system. The system gathers all the relevant inputs data (feed water turbidity,  $TMP_{ol}$ , m and  $\alpha$ ) for at least 20 minutes before all these data were sent to the ANN controller for the estimation of  $T_{fil}$ . Once the  $T_{fil}$  for a particular filtration sequence has been estimated, the filtration sequence shall be initiated when the filtration sequence ceased. Figure 7.7 shows the block diagram of the ANN controller number 1 utilized in the process control.



Figure 7.7: Block diagram of ANN controller number 1

Once the filtration sequence has been completed, the ANN controller number 2 shall be initiated to commence the backwash sequence. During the backwash sequence, the flow of water was reversed as opposed to the filtration sequence to dislodge the foulant from the membrane pores and surface as illustrated in Figure 7.1. Clean water enters at the filtrate port of the UF membrane module and discharged through the inlet port to the drain by switching the control valves shown in Figure 7.4. The hydraulic pressure generated during backwash is known as reverse TMP (the difference of pressure between filtrate port and inlet port of the UF membrane module during backwash sequence) or  $TMP_{rev}$  as the flow of water is from the opposite direction compared to the filtration sequence. Related inputs data such as on-line  $TMP_{rev}$  and the total volume of clean water utilized during backwash ( $V_{bw}$ ) were fed into the ANN controller number 2 to determine the duration of the backwash. Since the backwash sequence normally last 60 seconds or less, the inputs data ( $TMP_{rev}$  and  $V_{bw}$ ) were fed into the SCADA system every second and the controller decides whether to continue or stop the sequence every second as well. Once the controller has decided to end the backwash sequence then the filtration sequence would be re-initiated again and the whole cycle was repeated until chemical cleaning of the membrane was required.

During the filtration sequence, the designated control valves were opened and the feed pump starts. There were only two possible outputs from ANN controller number 1 which were to continue or cease the filtration sequence. Once the controller produced an output to cease the filtration sequence, the feed pump stops and the all the control valves were closed. Completion of the filtration sequence would trigger on the initiation of the ANN controller number 2 to commence with the backwash sequence. The designated control valves opened and the backwash pump starts to commence the backwash sequence. Similarly there were only two outputs from this controller number 2 ceases the backwash sequence, once the ANN controller number 2 ceases the backwash sequence, the next filtration sequence begins and the cycle shall be repeated. Figure 7.8 shows the whole process control architecture using the ANN predictive model and controllers.



Figure 7.8: Architecture of ANN process control loop

## 7.3.2.3 Conventional set-points and ANN control systems

Implementation of both the ANN and conventional set-points control systems required the same final control elements (control valves and pumps) and sensors (pressure transmitters). The main differences between these two control systems were the durations of the filtrate and backwash sequences. In the conventional set-points control system, both the filtration and backwash durations were pre-determined irrespective of the feed water characteristics such as turbidity and feed water solids concentrations. The ANN control system requires information of the feed water turbidity to determine the potential membrane fouling propensity represented by the product of  $\alpha c_s$ .

Low turbidity feed water has less fouling potential than higher turbidity feed water on the UF membrane. Based on this assumption, feed water with low turbidity could be under filtration sequence for a longer period of time before a backwash is initiated. The amount of water losses through backwash could be reduced significantly when the UF system is treating low turbidity of feed water. During backwash sequence, the reverse TMP ( $TMP_{rev}$ ) data indicates how much solids have accumulated on the membrane surface. The higher  $TMP_{rev}$  during backwash shows higher resistance which represents more accumulation of solids/foulant on the membrane. Similarly the total volume of clean water utilized during the backwash sequence ( $V_{bw}$ ) provides information on how much cleaning have been done on the membrane.

The ANN control system is an alternative method that is suitable for implementation at industrial-scale UF membrane water treatment system to reduce water losses through backwash. Under the conventional set-points control, water losses remain the same irrespective of the feed water characteristic changes. The ANN control system has the advantage of reducing water losses through longer filtration durations if the feed water has lower potential membrane fouling propensity (such as lower turbidity and solids concentrations). Furthermore the ANN control system would allow much longer backwash duration if the membrane has accumulated more solids on its surface than expected based on the on-line  $TMP_{rev}$  data. Re-training of the ANN model and controllers with updated data such as feed water characteristics and TMP profiles enable the system to "re-learn" the new patterns to suit current operational conditions.

## 7.4 Results and discussions

The details results of the conventional set-points and ANN control systems were further examined with the necessary analysis. All the experiments conducted using the UF experimental system utilized feed water from the same river source. Set-points (filtration and backwash durations) of the conventional control implemented on the UF experimental system were similar to the industrial-scale UF membrane water treatment plant mentioned earlier in the case studies. This allows a close representation of the industrial-scale UF system by using the same feed water source and similar UF membrane in a smaller scale.

Data collection using the UF experimental system was initially conducted to gather the required information to train the ANN model and controllers. Different feed water samples with various turbidities were fed into the system for 60 minutes of filtration duration to obtain the TMP profiles. These data were recorded digitally in the SCADA system during the experiments. Laboratory analysis to determine the solids concentrations of the feed water samples were also conducted. After the training and validation of the neural networks, the ANN control system was implemented on-line with the UF experimental system. Both the conventional set-points and the ANN control systems results were compared and analyzed.

## 7.4.1 Results of the conventional set-points control system

As mentioned earlier, the set-points implemented on the UF experimental system were similar to the industrial-scale UF membrane water treatment plant in the previous case studies. These set-points include the filtration and backwash durations operating under the dead-end constant flux filtration mode. Table 7.1 shows the operational parameters of the UF experimental system. Both the filtration and backwash fluxes of the UF experimental system were similar to the industrial-scale UF membrane water treatment system. The major differences between these two systems were smaller membrane surface area was utilized in the UF experimental system (1 m<sup>2</sup>) compared to 7, 200 m<sup>2</sup> for the industrial-scale system.

Parameters	UF experimental system	
Type of UF membrane	Hollow fibre (mPES)	
Feed water source	Natural river water	
Membrane surface area	$1 \text{ m}^2$	
Filtration flux	80 L/m <sup>2</sup> hr	
Backwash flux	230 L/m <sup>2</sup> hr	
Filtration duration	30 minutes	
Backwash duration	60 seconds	

Table 7.1: Operational conditions and parameters of the UF experimental system

All the required on-line operational data of the UF experimental system such as TMP profiles, filtration and backwash durations was recorded in the SCADA system. The conventional system commences with filtration sequence for 30 minutes followed by a 60 seconds backwash sequence. Feed water samples maintained the same turbidity throughout each filtration sequence. The maximum recommended feed water turbidity

to the industrial-scale UF membrane water treatment plant should not exceed 20 NTU which was also practiced on the UF experimental system. Typically the river water turbidity under clear weather conditions was on the average between 10 - 15 NTU which was very suitable for direct feed UF membrane systems. Two samples of feed water with 8 NTU and 18 NTU of turbidity were fed into the UF experimental system using the conventional set-points control system. The results of the TMP profiles were shown in Figure 7.9 and Figure 7.10 respectively.



Figure 7.9: TMP profile of feed water with 8 NTU of turbidity



Figure 7.10: TMP profile of feed water with 18 NTU of turbidity

Results from both TMP profiles in Figure 7.9 and Figure 7.10 indicated similar pattern during filtration and backwash sequences in 5 complete cycles. Initially all the profiles indicated TMP values of between 0.36 - 0.38 Bar and gradually increases to 0.41 - 0.43 Bar at the end of the filtration sequences. Under the conventional set-points control system, a 30 minutes filtration sequence followed by a 60 seconds backwash sequence was implemented for feed water samples of 20 NTU or below. After the backwash sequence, the initial TMP of the next filtration sequence was restored to between 0.36 - 0.38 Bar.

### 7.4.2 Gathering information and data for the ANN training

Prior to implementing the ANN control system, relevant data and information of the filtration, backwash and feed water characteristics were required. Literature has reported that both solids concentrations of feed water ( $c_s$ ) and the specific cake resistance during filtration ( $\alpha$ ) represents the potential membrane fouling propensity (Boerlage et al., 2004). Analysis of the feed water solids concentrations require almost 10 – 15 hours under the American Public Health Association (APHA) analysis method. A correlation between the turbidity and total feed water solids concentrations are usually established for rapid estimation of  $c_s$ . Data of feed water turbidity could be easily analyzed using laboratory turbidity analyzer within a minute and translated to  $c_s$  with the established correlation.

Figure 7.11 shows the data collected to establish the correlation between the total suspended solids (TSS) concentrations or  $c_s$  against the turbidity of the river water conducted in the year 2016. A linear correlation was established between  $c_s$  and the

turbidity of the river water in Figure 7.11. The values of  $c_s$  for different turbidity of feed water could be rapidly estimated by knowing the turbidity of the feed water.



Figure 7.11: Established correlation between  $c_s$  and turbidity of the river water

Differences in solids concentrations of the feed water samples implied that longer filtration duration might be applicable for feed water with low turbidity within the recommended potential membrane fouling propensity represented by the product of  $\alpha c_s$ . Benefit of extending filtration duration includes reducing significant amount of water losses through backwash. Various feed water turbidity samples (5 NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU) were collected from the river using the method described earlier. Each of the feed water samples was fed into the UF experimental system to obtain the TMP profiles up to 60 minutes under dead-end constant flux filtration. Figure 7.12 shows the TMP profiles for the various samples of feed water on the UF experimental system.



Figure 7.12: TMP profiles for various feed water samples

Results shown in Figure 7.12 indicated very little variations or differences in the TMP profiles for all the feed water samples of 5 NTU, 10 NTU, 15 NTU, 20 NTU and 25 NTU. Initially all the TMP profiles started off with values between 0.36 - 0.38 Bar in the first few minutes. The TMP increases gradually reaching between 0.46 - 0.49 Bar after 60 minutes of filtration. There was no significant TMP profiles difference observed in all the samples which means additional inputs data were necessary to be fed into the ANN controller number 1 for better control efficiency. The correlation between the filtration flux, TMP, specific cake resistance and solids concentrations of feed water could be established using the Darcy's equation (6.1) shown earlier in Chapter 6.

Value of membrane resistance or  $R_m$  was determined using normal experimental analysis procedures mentioned earlier (Boerlage et al., 1998; Pellegrin et al., 2015; Roy & De, 2015). Both  $\alpha$  and  $c_s$  have been mentioned in literature as filtration parameters which are complicated to be determined experimentally (Boerlage et al., 2004). The direct relationship between m and  $c_s$  has been shown in equation (6.3) at Chapter 6. Correlation shown in this equation indicated a direct relationship between  $c_s$  and m in dead-end constant flux filtration mode. Utilizing the  $c_s$  and turbidity correlation established in Figure 7.11, the relevant estimated values of  $c_s$  for the feed water samples was obtained as shown in Figure 7.13.



Figure 7.13: Estimated values of c<sub>s</sub> for various turbidity of feed water

It was important to emphasize that during filtration sequence, the values of m increased linearly with time as more solids/foulant were accumulated on the membrane surface as cake layer. Feed water with higher turbidity corresponds to higher solids loading or m values during filtration sequence. Figure 7.14 shows the gradual increase of m for the various feed water samples during the filtration sequence.



Figure 7.14: Data of *m* during filtration for various feed water samples

By having the relevant correlation and experimental data, all the parameters required in the Darcy' equation in equation (6.1) such as J,  $R_m$ ,  $\mu$ , m and  $\Delta P$  could be determined to estimate  $\alpha$ . Values of  $\alpha$  throughout the 60 minutes filtration sequence were estimated based on Darcy's law and presented in Figure 7.15.



Figure 7.15: Estimation of specific cake resistance during filtration sequence
It was shown in Figure 7.15 that all of the feed water samples exhibited values of decreasing  $\alpha$  during the initial 20 minutes of filtration and ultimately reaching a constant value. These ultimate values of  $\alpha$  increase as the turbidity of the feed water samples decrease. Similar results and observation was also reported in literature stating that the increase of  $\alpha$  values for decreasing solids concentrations of the feed solutions (Chang & Kim, 2005). It was suggested that for feed water samples with low solids concentrations, values of  $\alpha$  decrease with the increase of solids concentrations of the feed solutions of the feed solutions of the feed solutions the increase of  $\alpha$  decrease with the increase of solids concentrations of the feed solutions of the feed solutions (Chang & Kim, 2005). It was suggested that for feed water samples with low solids concentrations, values of  $\alpha$  decrease with the increase of solids concentrations of the feed solutions of the feed solutions the feed solutions during the cake layer consolidation stage.

Under the conventional set-points control system for the industrial-scale UF membrane water treatment plant, the filtration duration was pre-determined to last for 30 minutes before a 60 seconds backwash sequence ensues. The maximum feed water turbidity entering the UF system was limited to 20 NTU and below based on the initial design to ensure minimal irreversible membrane fouling potential. Similar set-points control with feed water samples of 20 NTU and below were carried out using the UF experimental system to mimic the same operational conditions. Utilizing results from the UF experimental system shown in Figure 7.12 and applying the Darcy' law in equation (6.1) and (6.3), the values of  $c_s$  and  $\alpha$  (Figure 7.13 and Figure 7.15 respectively) were calculated and presented in Table 7.2.

	20 NTU	5 NTU	10 NTU	15 NTU	25 NTU
$c_s$ (kg/m <sup>3</sup> )	0.02451	0.00596	0.01215	0.01833	0.03070
$\alpha$ (m/kg)	<b>3.42</b> X 10 <sup>14</sup>	13.85 X 10 <sup>14</sup>	6.79 X 10 <sup>14</sup>	$4.48 \ge 10^{14}$	2.67 X 10 <sup>14</sup>
$\alpha c_s$ (m <sup>-2</sup> )	8.38 X 10 <sup>12</sup>	8.25 X 10 <sup>12</sup>	8.24 X 10 <sup>12</sup>	8.21 X 10 <sup>12</sup>	8.20 X 10 <sup>12</sup>
Filtration	30 min	55 min	50 min	40 min	25 min
duration					

Table 7.2: Estimated values of  $c_s$  and  $\alpha$  for various feed water samples

Data shown in Table 7.2 highlighted that the 30 minutes filtration duration with the maximum recommended feed water turbidity of 20 NTU produced  $\alpha c_s$  of 8.38 X 10<sup>12</sup> m<sup>-2</sup>. The product of  $\alpha c_s$  was mentioned earlier to represent potential membrane fouling propensity and should be kept below a specific value to ensure minimal fouling potential (Boerlage et al., 2004). All the filtration data for the various feed water samples (5 NTU, 10 NTU, 15 NTU and 25 NTU) were also analyzed for their respective  $\alpha c_s$  values. Data shown in Table 7.2 indicated that experiments using feed water with turbidity lower than 20 NTU (such as 5 NTU, 10 NTU and 15 NTU) could continue with filtration for more than 30 minutes before their respective values of  $\alpha c_s$ reaching close to 8.38 X 10<sup>12</sup> m<sup>-2</sup>. Feed water sample with 25 NTU of turbidity could only undergo filtration duration of up to 25 minutes before reaching close to this value. Previous correlation of  $c_s$  and turbidity has indicated that higher feed water turbidity represents higher solids concentrations. Feed water samples with lower turbidity would then represent lower  $c_s$  values suggesting longer filtration duration is possible before reaching the recommended value of  $\alpha c_s$ . Examining the product of  $\alpha c_s$  is a more accurate analysis to determine the potential membrane fouling propensity compare to fixing a set-point of filtration duration for all feed water samples in the conventional control system. Figure 7.16 shows the estimated filtration duration against various feed water samples indicated in Table 7.2.



Figure 7.16: Correlation between filtration duration and feed water turbidity

In the conventional set-points control system, filtration duration has been fixed for all feed water turbidity of 20 NTU or below. A different approach was taken in the ANN control system whereby the values of  $\alpha c_s$  were taken into considerations for various feed water turbidities. Such approach provides an alternative method for process control by taking into consideration the values of  $c_s$  which were associated with the feed water characteristics and values of  $\alpha$  which were related to the filtration process or TMP. Figure 7.16 has indicated that the estimated filtration duration decreases when the feed water turbidity increases in order to maintain the  $\alpha c_s$  values close to 8.38 X 10<sup>12</sup> m<sup>-2</sup>.

## 7.4.3 Results of the ANN control system

After gathering all the necessary laboratory analysis and on-line data from the UF experimental system, the ANN model and controllers were trained with these data. There are three ANN model and controllers which were trained with these data:-

- 1. ANN predictive model to estimate values of  $\alpha$
- 2. ANN controller number 1 to control the filtration duration
- 3. ANN controller number 2 to control the backwash duration

Details of the ANN predictive model development procedures have been highlighted in Chapter 6. Estimated values of  $\alpha$  from the ANN predictive model were used as one of the continuously fed inputs to the ANN controller number 1. Information from Figure 7.12, Figure 7.13, Figure 7.14, Figure 7.15 and Figure 7.16 were scaled and arranged accordingly for utilization as training data for the ANN controller number 1. The outputs from the ANN controller number 1 should provide information to either continue with the filtration sequence (represented by "1") or cease filtration (represented by "0"). Once the output from ANN controller number 1 have indicated "0" or cease filtration, signal shall be send to ANN controller number 2 to commence the backwash sequence.

Similarly the ANN controller number 2 has been trained with the relevant data  $(TMP_{rev} \text{ and } V_{bw})$  to ensure sufficient cleaning of the membrane during the backwash sequence. During the backwash sequence, on-line data of the reverse TMP or  $TMP_{rev}$  was taken into consideration to ensure the backwash or cleaning was effective with the lowering of resistance (represented by declining values of  $TMP_{rev}$ ) after a certain period

of duration. Initially during the backwash, the  $TMP_{rev}$  values would be higher due to accumulation of solids on the membrane surface. As the backwash progresses, the TMP<sub>rev</sub> data shall further decreases indicating the solids cake layer has been removed from the membrane surface so the backwash sequence should be stopped and the next filtration sequence could proceed. The total volume of water used during backwash  $(V_{bw})$  was also an important input fed into the ANN controller number 2. Under normal conditions the final value of  $V_{bw}$  would be the same for each backwash sequences because prior filtration sequences determined by ANN controller number 1 pose similar potential membrane fouling propensity ( $\alpha c_s$ ). The ANN controller number 2 determines the backwash duration by recognizing the  $TMP_{rev}$  has stabilized with the estimated  $V_{hw}$ and ceases the backwash sequence. Subsequently the next filtration sequence commences until reaching another backwash sequence. Table 7.3 shows the inputs and outputs of all the ANN model and controllers. As mentioned earlier, the filtration flux was assumed to be constant as long as the tolerance was within  $\pm 10\%$  of the desired values. During the initial stage of the filtration sequence, there was less resistance caused by accumulation of solids on the membrane compared to the end of the filtration sequence. The initial filtration flow rate would be higher and gradually decreases. Efforts were taken to ensure that the flow rate during the whole filtration sequence still maintains between  $\pm 10\%$  of the desired value. Similarly during backwash sequence the flow rate was measured volumetrically to ensure tolerance of  $\pm 10\%$  of the desired value throughout the sequence.

	Ing	outs	Outputs
	Parameter	Source	Parameter
ANN predictive model	Feed water turbidity	Laboratory turbidity analyzer	Estimated current value of $\alpha$ ( $\alpha_t$ )
	On-line TMP ( <i>TMP</i> <sub>ol</sub> )	On-line pressure transmitters signal to SCADA system	
	Filtration time	Timer from SCADA system	
	Past values of $\alpha$ ( $\alpha_{t-1}$ )	Feedback from SCADA system	
ANN controller number 1	Feed water turbidity	Laboratory turbidity analyzer	Filtration duration or $T_{fil}$ .
(filtration sequence)	On-line TMP ( <i>TMP</i> <sub>ol</sub> )	On-line pressure transmitters signal to SCADA system	If filtration time $< T_{fil}$ then "1" to continue
	Mass of cake per filter area ( <i>m</i> )	Correlation from Figure 7.11 and equation (6.3)	filtration. If filtration time $\geq$ $T_{fil}$ then "0" to stop
	Estimated current values of $\alpha$ ( $\alpha_t$ )	Output from ANN predictive model	filtration
ANN controller number 2	Reverse TMP ( <i>TMP</i> <sub>rev</sub> )	On-line pressure transmitters signal to	"1" to continue or "0" to stop
(backwash sequence)		SCADA system	backwash
	Total volume of backwash water used	Timer from SCADA system (assuming	
	$(V_{bw})$	constant flow rate from backwash pump)	

Table 7.3: Inputs and outputs of the ANN model and controllers

The three ANN model and controllers were trained individually with the inputs and outputs data shown in Table 7.3 and validated with other unseen data. These three ANN model and controllers were developed in the SCADA software environment and ready to be implemented on-line for actual process control on the UF experimental system. Feed water with turbidity of 8 NTU was fed into the UF experimental system using the ANN control system. The on-line TMP during filtration sequence indicated a gradual increase of pressure from 0.37 Bar to 0.46 Bar as shown in Figure 7.17 (a). In the figure, filtration duration controlled by ANN controller number 1 continues for 50 minutes before a backwash was initiated. The backwash sequence controlled by ANN controller

number 2 takes about 51 seconds to complete before another filtration sequence was initiated. When the next filtration sequence commences, the initial TMP returns back to 0.37 Bar which indicated an almost complete removal of the accumulated solids on the membrane surface during the last backwash sequence. In Figure 7.17 (b), the values of  $\alpha$  remains almost at a constant value of 8.52 X 10<sup>14</sup> m/kg after the initial 10 minutes representing consolidation of the cake layer throughout the filtration sequence. The output of ANN controller number 1 was shown in Figure 7.17 (c). In all the 5 filtration sequences tested using the controller with the 8 NTU feed water, the filtration duration was averagely 50 minutes which was very close to the estimated duration of 51 minutes shown on Figure 7.16. The output of ANN controller number 2 was shown on Figure 7.17 (d) which indicated an average 51 seconds of backwash duration.

Results obtained from using the feed water of 8 NTU indicated that the filtration sequence could be extended up to 50 minutes followed by a 51 seconds of backwash sequence without causing any increase of TMP in the following next filtration sequence. This was also in agreement with the data obtained in Table 7.2 indicating that for feed water with lower turbidity, longer filtration duration was possible while ensuring  $\alpha c_s$  close to the recommended value of 8.38 X 10<sup>12</sup> m<sup>-2</sup>. As mentioned earlier, the product of  $\alpha c_s$  is an indication of potential membrane fouling propensity which should be kept close to the recommended value.



Figure 7.17 (a) TMP profiles during filtration (8 NTU sample)



Figure 7.17 (b) Output from ANN predictive model (8 NTU sample)



Figure 7.17 (c) Output from ANN controller number 1 – filtration sequence (8 NTU sample)



Figure 7.17 (d) Output from ANN controller number 2 – backwash sequence (8 NTU sample)

The filtration and backwash sequences using the ANN control system was repeated for 5 cycles to determine its consistency with the 8 NTU feed water. Table 7.4 shows the results of the 5 cycles.

	1 <sup>st</sup> cycle	2 <sup>nd</sup> cycle	3 <sup>rd</sup> cycle	4 <sup>th</sup> cycle	5 <sup>th</sup> cycle	Average
Initial TMP (Bar)	0.37	0.36	0.38	0.38	0.37	0.37 Bar
Final TMP (Bar)	0.46	0.46	0.45	0.46	0.46	0.46 Bar
α ( X 10 <sup>14</sup> m/kg)	8.52	8.51	8.53	8.51	8.53	8.52
$c_s$ (X 10 <sup>-3</sup> kg/m <sup>3</sup> )	9.67	9.67	9.67	9.67	9.67	9.67
$\alpha c_{s}$ (X 10 <sup>12</sup> m <sup>-2</sup> )	8.24	8.23	8.25	8.23	8.25	8.24
Filtration duration (min)	50	51	50	51	50	50
Backwash duration (s)	50	51	51	50	51	51

Table 7.4: Results for the 8 NTU feed water sample

Similar experiments were applied on feed water with much higher turbidity at 18 NTU using the same ANN control system. When the filtration sequence was initiated using the higher turbidity feed water sample, the initial TMP was 0.37 Bar and gradually increases to 0.42 Bar. Total duration for the filtration sequence was 31 minutes before a backwash sequence was initiated. The estimated  $\alpha$  for this 18 NTU sample feed water was 3.64 X 10<sup>14</sup> m/kg which were lower than the 8 NTU sample of 8.52 X 10<sup>14</sup> m/kg. Even though the value of  $\alpha$  was lower, the  $c_s$  value of the 18 NTU sample was much higher because of the higher solids concentrations. The filtration duration of 31 minutes control by ANN controller number 1 was quite close to the estimated filtration duration of 34 minutes indicated in Figure 7.16. After the

completion of the filtration sequence, the ANN controller number 2 takes over to commence the backwash sequence. The total backwash duration was 51 seconds which was similar to the 8 NTU sample. This was because both the filtration sequences for the 8 NTU and 18 NTU samples stopped when the  $\alpha c_s$  values were close to 8.38 X 10<sup>12</sup> m<sup>-2</sup>. So this has suggested that both the filtration sequences with the 8 NTU and 18 NTU samples controlled by ANN controller number 1 have similar potential membrane fouling propensities and required the same backwash duration to dislodge the solids from the membrane surface.

Similar to the previous sample, the 18 NTU sample was repeated for 5 cycles of filtration and backwash sequences to determine the controllers' consistency. The average values of  $\alpha c_s$  for the 18 NTU sample was 8.03 X 10<sup>12</sup> m<sup>-2</sup> which was quite close to the recommended value of 8.38 X 10<sup>12</sup> m<sup>-2</sup> as well. After each backwash sequences, the initial TMP of the next filtration sequence returns to between 0.37 – 0.38 Bar. This indicated an almost complete removal of the solids cake layer from the membrane surface after each backwash sequences. Figure 7.18 shows the results of the 18 NTU sample using the ANN control system. Table 7.5 shows the operational results of 5 cycles with the ANN control system on the 18 NTU feed water sample.







Figure 7.18 (b) Output from ANN predictive model (18 NTU sample)



Figure 7.18 (c) Output from ANN controller number 1 – filtration sequence (18 NTU sample)



Figure 7.18 (d) Output from ANN controller number 2 – backwash sequence (18 NTU sample)

	1 <sup>st</sup> cycle	2 <sup>nd</sup> cycle	3 <sup>rd</sup> cycle	4 <sup>th</sup> cycle	5 <sup>th</sup> cycle	Average
Initial TMP (Bar)	0.37	0.37	0.38	0.37	0.37	0.37 Bar
Final TMP (Bar)	0.41	0.42	0.43	0.42	0.42	0.42 Bar
$\alpha$ (X 10 <sup>14</sup> m/kg)	3.64	3.65	3.66	3.64	3.64	3.64
$(X 10^{-3} \text{kg/m}^3)$	22.04	22.04	22.04	22.04	22.04	22.04
$\alpha c_{s}$ (X 10 <sup>12</sup> m <sup>-2</sup> )	8.02	8.04	8.07	8.02	8.02	8.03
Filtration duration (min)	32	32	31	31	31	31
Backwash duration (s)	50	51	51	50	51	51

 Table 7.5: Results for the 18 NTU feed water sample

It was mentioned earlier that all the ANN model and controllers were trained using data obtained from filtration and backwash sequences for feed water samples with turbidities range from 5 NTU to 25 NTU. The intention of training the ANN model and controllers within this range was to correspond to the industrial-scale UF membrane water treatment plant limit of processing river water with maximum recommended turbidity of 20 NTU. Typically the river water turbidity was between 10 - 15 NTU. Direct feed UF system is basically suitable for low turbidity of natural surface water.

Efforts were taken to test the ANN control system beyond the training data with 30 NTU of feed water. Table 7.6 shows the results of using a 30 NTU feed water sample with the ANN control system. The filtration and backwash sequences were repeated 5 cycles similar to the previous two feed water samples of 8 NTU and 18 NTU.

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

Table 7.6: Results for the 30 NTU feed water sample

The data shown in Table 7.6 indicated that the average filtration duration allowed by ANN controller number 1 was 24 minutes. By extrapolating the graph on Figure 7.16, the estimated filtration duration should be 20 minutes for a 30 NTU feed water sample. The ANN controller number 1 was still able to reduce the filtration duration of the 30 NTU sample to 24 minutes even though it was not trained with the data. It is important to ensure that the working range of the ANN control system falls within the range of the training data for optimum performance.

If there are significant changes on the feed water  $c_s$  and turbidity correlation, the estimated values of  $\alpha c_s$  might have differed from the initial training data and much higher fouling propensity might occurs on the membrane surface before a backwash sequence is initiated. The ANN controller number 2 should allow longer backwash duration in case such abnormal condition occurs during the previous filtration sequence. Such abnormal condition with much higher amount of accumulated solids than expected during filtration was used to train the ANN controller number 2. The reverse TMP (*TMP<sub>rev</sub>*) during backwash sequence is an important aspect to indicate the amount of accumulated solids on the membrane surface during the previous filtration sequence.

resistance caused by the cake layer on the membrane. Higher value of  $TMP_{rev}$  reading indicates higher resistance caused by the cake layer on the membrane surface which increases the backwash hydraulic pressure.

Under normal conditions, the values of  $\alpha c_s$  should be approximately 8.38 X 10<sup>12</sup> m<sup>-2</sup> at the end of the filtration sequence. The characteristics changes of the river water might altered the  $c_s$  and turbidity correlation (Figure 7.11) and causes significantly higher values of  $\alpha c_s$  which were different than the training data used to train the controller. This resulted in higher potential membrane fouling propensity on the membrane with more accumulation of solids at the end of the filtration sequence than expected.

The higher potential membrane fouling propensity was simulated by feeding in a 30 NTU feed water sample into the UF experimental system while entering 8 NTU as the feed water turbidity in the SCADA system. Data shown in Figure 7.16 and Table 7.4 indicated that for a feed water sample with 8 NTU, the filtration duration would be 50 – 51 minutes followed by a 51 seconds of backwash duration under normal conditions. Even though the actual feed water sample was 30 NTU, it was entered as 8 NTU in the SCADA system so the ANN controller number 1 would have allowed up to 50 minutes of filtration duration before initiating the backwash sequence. Once the backwash sequence was initiated, the on-line reverse TMP (*TMP<sub>rev</sub>*) data was fed into the ANN controller number 2 to determine the backwash duration required. Due to the higher potential membrane fouling propensity for the 30 NTU feed water sample accumulated during the filtration sequence, a much higher resistance would be observed during the initial backwash sequence which was reflected in the *TMP<sub>rev</sub>* profile. Figure 7.19 shows the *TMP<sub>rev</sub>* profiles as well as the ANN controller number 2 outputs for both the 8 NTU and 30 NTU feed water samples during backwash sequences.



Figure 7.19 (a) TMP<sub>rev</sub> profile for 8 NTU

Figure 7.19 (b) TMP<sub>rev</sub> profile for 30 NTU



Figure 7.19 (c) Outputs from ANN controller number 2 for 8 NTU

Figure 7.19 (d) Outputs from ANN controller number 2 for 30 NTU

Figure 7.19: *TMP<sub>rev</sub>* profiles and ANN controller number 2 outputs

Figure 7.19 (a) shows the  $TMP_{rev}$  profile of the 8 NTU feed water sample was initially about 1.7 Bar and gradually decreases to 1.6 Bar at the end of the backwash sequence. Figure 7.19 (c) shows the ANN controller number 2 outputs for this feed water sample which ceased the backwash sequence after 51 seconds. As mentioned earlier, to simulate higher potential membrane fouling propensity, a 30 NTU sample was fed into the UF experimental system by entering it as 8 NTU in the SCADA system. Figure 7.19 (b) shows the  $TMP_{rev}$  profile of the 30 NTU sample during the

backwash sequence. The initial  $TMP_{rev}$  for this 30 NTU sample was much higher at 1.9 Bar and subsequently decreases to 1.6 Bar after 62 seconds of backwash duration as shown in Figure 7.19 (d).

ANN controller number 2 has exhibited its capability to distinguish between different  $TMP_{rev}$  profiles to allow longer backwash duration for abnormal condition such as the 30 NTU sample. The extended or much longer backwash duration exceeding 55 seconds serves as an early indication or warning to the operator of the UF system that the characteristics of the river water might have changed. Gathering new data to re-establish the  $c_s$  and turbidity correlation as well as re-training all the ANN model and controllers might be required.

## 7.4.4 Analysis of the conventional and ANN control systems

After obtaining the results from both the conventional and ANN control systems, a comparison was established and presented. Table 7.7 shows the details and comparison between the two control systems. The comparisons were made under dead-end constant flux filtration operation mode for both the control systems.

Parameters	<b>Conventional control</b>	ANN control	
Filtration duration			
8 NTU (Feed water)	30 minutes	50 minutes	
18 NTU (Feed water)	30 minutes	31 minutes	
Fouling propensity( $\alpha c_s$ )			
8 NTU (Feed water)	$8.38 \times 10^{12} \text{ m}^{-2}$	$8.24 \text{ X} 10^{12} \text{ m}^{-2}$	
18 NTU (Feed water)	(based on 20 NTU only)	$8.03 \times 10^{12} \text{ m}^{-2}$	
Water losses (backwash)			
8NTU (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	

Table 7.7: Comparison of results between control systems

Summarized comparison shown on Table 7.7 indicated that the ANN control system was capable to regulate filtration durations of different feed water turbidity (8 NTU and 18 NTU) to ensure the potential membrane fouling propensity ( $\alpha c_s$ ) maintained at less than 8.38 X 10<sup>12</sup> m<sup>-2</sup>. The value of 8.38 X 10<sup>12</sup> m<sup>-2</sup> was taken as a reference point by using a 20 NTU feed water sample for filtration of 30 minutes in the conventional control system. It has been mentioned earlier that irrespective of the feed water turbidity (20 NTU or below) the conventional system would allowed 30 minutes of filtration duration followed by a 60 seconds of backwash duration. This translates to constant water losses of 9.6% for the conventional system irrespective of the feed water filtration sequence with initial TMP of between 0.36 – 0.38 Bar which indicates a clean membrane surface has been restored after the backwash.

The ANN control system exhibited a few advantages over the conventional system. During the filtration sequence, the ANN predictive model was constantly predicting the values of  $\alpha$  which were dependence of the feed water characteristics. The estimated values of  $\alpha$  allowed rapid prediction of the potential membrane fouling propensity ( $\alpha c_s$ ) to ensure it was approximately the recommended value 8.38 X 10<sup>12</sup> m<sup>-2</sup> at the end of the filtration sequence. The conventional control system does not depend on the values of  $\alpha c_s$  and fixed the filtration duration as 30 minutes for all feed water turbidities. Results of the experiments indicated that the ANN control system allowed feed water with lower turbidity to undergo longer filtration duration while the higher turbidity feed water would have shorter filtration duration to ensure the recommend value of  $\alpha c_s$  at the end of the filtration sequence.

Once the filtration sequence was completed, ANN controller number 2 would take control of the backwash sequence. Under normal conditions, at the end of the filtration sequence the values of  $\alpha c_s$  for all the feed water samples would be approximately 8.38 X  $10^{12}$  m<sup>-2</sup>. Typically the backwash duration would be around 50 – 51 seconds before the commencement of the next filtration sequence. Allowing longer filtration duration with similar backwash duration reduces water losses significantly when filtering lower turbidity of feed water (such as the 8 NTU sample). The water losses for the 8 NTU sample was only 4.9% compare to 9.6% for the conventional system. As for the 18 NTU sample there was only marginal difference on the water losses for both control systems because both the filtration and backwash durations were almost similar. The initial TMP after each backwash for both control systems were between 0.36 – 0.38 Bar which indicated that the membrane has been thoroughly cleaned after the backwash.

## 7.5 Comparisons between conventional and ANN control systems

The ANN control system provides an alternative method for the UF system with the possibility of reducing water losses for low turbidity of feed water. It was also suggested that the correlation of the  $c_s$  and turbidity of the feed water is required to be updated regularly as any significant changes might require re-training of all the ANN model and controllers. Skilled and competence operators are required for these tasks. Having unreliable  $c_s$  and turbidity correlation would cause the estimated  $\alpha c_s$  to be less accurate and increasing the chances of higher potential membrane fouling propensity.

Ensuring minimal capital expenditure on the control system upgrades remains a priority to ensure commercial sustainability. The ANN control system is an alternative control strategy which utilizes commonly used on-line data and simple laboratory analysis to reduce water wastages and ensuring acceptable potential membrane fouling propensity. It is not a control system to eliminate membrane fouling. Table 7.8 summarized the main differences between the conventional and ANN control systems.

	<b>Conventional control</b>	ANN control
Advantages	<ul> <li>Ease of implementation with pre-determined set-points using PLC, minimal operator's intervention (Alphonsus &amp; Abdullah, 2016).</li> <li>Widely implemented on industrial-scale UF membrane water treatment plants operating under deadend filtration mode with intermittent backwash sequence (Cogan &amp; Chellam, 2014)</li> </ul>	<ul> <li>Reduction of water losses with longer filtration duration for feed water with low turbidity.</li> <li>Prediction of potential membrane fouling propensity of various feed water turbidity</li> </ul>
Disadvantages	<ul> <li>Fixed amount of water losses through pre-determined backwash flow rate and duration (Remize et al., 2010).</li> <li>Unable to predict potential membrane fouling conditions due to feed water characteristics changes (Shetty &amp; Chellam, 2003).</li> </ul>	<ul> <li>Required constant monitoring of the feed water characteristics changes and re-training of the ANN model and controllers.</li> <li>Not a common control system and require skilled personnel to monitor and validate any required changes</li> </ul>

Table	7.8:	<b>Summary</b>	of the	convention	al and	ANN	control s	systems
		•						•/

# 7.6 Summary

In this chapter an alternative control system utilizing ANN model and controllers have been developed for the dead-end constant flux UF process. This ANN control system was compared with the conventional set-points control system. The ANN control system provides a few advantages over the conventional control system such as being able to estimate the potential membrane fouling propensity ( $\alpha c_s$ ) and reducing water losses for feed water with low turbidity. This ANN control system provides an alternative method to reduce water losses with certain limitations. The characteristic changes of the feed water would require gathering of updated data to re-train all the ANN model and controllers for optimum performance.

### **CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS**

In this final chapter, summary findings of the research work and conclusions have been highlighted. The achievements of the five objectives in this research were further elaborated. Recommendations on possible future research work relevant to this current study have also been suggested.

## 8.1 Findings and conclusions

The main objectives of this research encompassed various aspects of evaluations, modelling and control of ultrafiltration membrane water treatment systems. In the first objective, efforts were made to present a case study of an industrial-scale UF membrane water treatment plant in Malaysia. This treatment plant was commissioned in 2013 to provide safe potable water through the public-piped water supply system to a nearby township. Both the operational and design criteria such as membrane surface area, feed water characteristics, chemicals for UF membrane cleaning, membrane fouling, electricity consumption, hydraulic backwash and chemicals cleaning efficiency were analyzed in details. These actual issues encountered at the UF membrane water treatment plant was examined with information obtained from literature. Detailed analyses have indicated that most of these highlighted issues have been documented in literature and possible solutions were suggested. This case study has elucidated that practical and effective solutions could be obtained from literature for more effective design and operation of industrial-scale UF membrane water treatment plants.

Various aspects of two industrial-scale water treatment systems were investigated under the second objective. A detail case study was conducted to compare both the industrial-scale UF membrane and conventional media/sand filtration water treatment systems. Five aspects of evaluation which encompassed capital cost, operational cost, maintenance cost, filtrate quality and overall water losses were highlighted for both systems. The overall cost or commercial aspects of the conventional media/sand filtration system were still much lower than the UF system. In terms of the filtrate quality, the UF system produced consistently better filtrate. Water losses from the conventional system were much lower compared to the UF system. Sludge discharged from the conventional system was heavily polluted by Aluminium based coagulant which posed serious environmental impact compared with the non-chemical polluted sludge from the UF system. The overall current cost of UF system was still much higher than the conventional system but the former could produce consistently much better filtrate quality and less harmful sludge to the environment. Further efforts to reduce the overall cost of the UF systems would enable this technology to be more feasible in the near future.

In the third case study, operational results from three different capacities of UF systems representing laboratory-scale, pilot-scale and industrial-scale systems were analyzed. Through this case study, it has been found that certain information from the UF experimental systems (laboratory-scale and pilot-scale) such as filtrate quality provides an accurate representation of the industrial-scale system. Other information from the experimental systems such as UF module design, TMP through membrane modules, feed pump efficiency and specific electricity utilization differs significantly than the industrial-scale system. Although the absolute values of TMP differ, all three UF systems exhibited similar TMP profiles pattern. These results provide a comprehensive analysis to ensure more precise information extraction and interpretation from these experimental systems to scale-up an industrial-scale UF system.

A pilot-scale UF system has been designed to collect the necessary filtration data of the dead-end constant flux UF process. These data were utilized to develop a hybrid model for the process. This hybrid model consists of a first principle model using Darcy's law and an artificial neural networks (ANN) predictive model to estimate two potential membrane fouling parameters. Firstly the specific cake resistance ( $\alpha$ ) was predicted using the ANN model and subsequently this parameter was applied into the first principle model to estimate the solids concentrations of the feed water ( $c_s$ ). The hybrid model provides an alternative method by using only commonly available on-line data and simple laboratory analysis to rapidly estimate these two parameters which could fluctuate significantly due to characteristics changes of the natural feed water. Regular monitoring of these estimated parameters allows preventive actions to be taken when there is significantly high potential membrane fouling propensity detected in the process.

In the final objective of the research, an UF experimental system was designed and commissioned to conduct on-line experiments on both the conventional set-points and ANN control systems. The ANN control system which consists of a predictive model and two controllers were developed and implemented on-line. Similar experiments were conducted using the conventional set-points control system to compare the efficiencies of both control systems. The conventional set-points control system exhibited similar water losses for all feed water samples of 20 NTU and below. Experimental results using the ANN control system indicates the advantage of water losses reduction for feed water samples of low turbidity. The ANN control system also provides information on the estimated potential membrane fouling propensity of the feed water samples. This alternative ANN control system has the potential to reduce the overall water losses from an UF membrane water treatment system with fluctuating feed water turbidity under the dead-end constant flux operation mode.

## 8.2 Contributions and novelty of the study

Although many research studies have been conducted on UF water treatment systems, they mostly concentrate on laboratory experiments and pilot-scale studies. This research study delves into industrial-scale UF membrane system with three case studies on an actual UF membrane water treatment plant in Malaysia. Practical performance analyses and evaluations have been conducted on this UF membrane water treatment plant. This process of highlighting the "real" issues and suggesting possible solutions are much needed by industrial-scale UF membrane water treatment plants' stakeholders. Comparisons involving various aspects of the UF and conventional media/sand filtration water treatment systems were also investigated to present the important information for further evaluations.

One of the most prominent problems in engineering design is scaling-up processes from laboratory experiments and pilot-scale results. In this research, efforts have been taken to provide insights on the interpretation of data obtained from laboratory-scale and pilot-scale experiments to scale-up an UF membrane water treatment plant. Analysis and comparison on the operational data of the laboratory-scale, pilot-scale and industrial-scale UF membrane water treatment systems enable better and more precise information interpretation to scale-up the system.

A practical hybrid model developed in this research is specifically targeted for industrial-scale UF membrane water treatment plants. This practical modelling approach provides a method for predicting potential membrane fouling parameters without using the laborious procedures required in the conventional analysis procedures. An artificial neural networks (ANN) control system based on this modelling approach has been developed and implemented on-line for the UF process to reduce water losses.

The overall scopes of this research work are to evaluate UF membrane water treatment systems and developed a practical process model as well as control system for the UF process. Information generated from this research work enables better comprehension on the UF membrane water treatment systems and applicable solutions to ensure this technology becomes more viable.

### 8.3 **Recommendations for future research works**

This research work encompassed evaluation of case studies, development of a hybrid model and alternative process control of the UF membrane water treatment systems. Various practical aspects of the UF membrane water treatment systems have been highlighted and investigated under this study. It is envisaged that the information elaborated in this research works could provide some alternative practical solutions to further improve the UF membrane water treatment systems. Several suggestions or recommendations for future research works related in this field of study are highlighted as follow:-

- Evaluation of case study on other possible alternative methods to further reduce the operational expenditure of the UF processes with renewable energy resources such as solar or wind power. Case study on actual return of investment (ROI) of using such renewable energy sources and the environmental impacts compare to conventional fossil fuel electricity generation is highly beneficial for stakeholders of industrial-scale water treatment plants.
- 2. Modelling of the UF process which takes into consideration the irreversible fouling of the membrane. Although much more extensive efforts are required to include the gradual increase of irreversible fouling into the model, it is more

relevant for long term operations. The inclusion of gradual irreversible fouling layer on the membrane would allow a more comprehensive study on the minimal frequency of rigorous chemical cleaning such as clean in place (CIP) procedures which are undesirable as it might potentially deforms the membranes.

3. Beside the hydraulic backwash cleaning presented in this research, further studies on alternative control systems which could increase the efficiency of chemical cleaning procedures should also be investigated. The standard chemical enhanced backwash (CEB) procedures utilizing conventional set-points control might not perform optimally under various feed water characteristics. Alternative process control systems utilizing sufficient but not excessive chemical to maximize cleaning efficiency on the membrane are highly beneficial commercially as well as ensuring minimal environmental impacts.

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## LIST OF PUBLICATIONS AND PAPERS PRESENTED

## **ISI-Cited Journal Articles**

- 1. Chun Ming Chew, M.K. Aroua, & M.A. Hussain (2017). A practical hybrid modelling approach for the prediction of potential fouling parameters in ultrafiltration membrane water treatment plant. *Journal of Industrial and Engineering Chemistry*, 45, 145 155.
- 2. Chun Ming Chew, M.K. Aroua, & M.A. Hussain (2016), Key issues of ultrafiltration membrane water treatment plant scale-up from laboratory and pilot plant results, *Water Science and Technology: Water Supply*, 16(2), 438 444.
- Chun Ming Chew, M.K. Aroua, M.A. Hussain, & W.M.Z. Wan Ismail (2016), Evaluation of ultrafiltration and conventional water treatment systems for sustainable development: an industrial scale case study, *Journal of Cleaner Production*, 112, 3152 – 3163.
- Chun Ming Chew, M.K. Aroua, M.A. Hussain, & W.M.Z. Wan Ismail (2015), Practical performance analysis of an industrial-scale ultrafiltration membrane water treatment plant, *Journal of the Taiwan Institute of Chemical Engineers*, 46, 132 – 139.
- 5. Chun Ming Chew, M.K. Aroua & M.A. Hussain (2017), Advanced process control for ultrafiltration membrane water treatment system, *Journal of Cleaner Production* (*Under review*)

## International Conference/Symposium Articles

- Chun Ming Chew, M.K. Aroua, M.A. Hussain, A novel filtration model for industrial-scale ultrafiltration membrane water treatment plant, 12<sup>th</sup> World Filtration Congress, 11<sup>th</sup> – 15<sup>th</sup> April 2016, Taipei International Convention Centre, Taiwan
- Chun Ming Chew, M.K. Aroua, M.A. Hussain, Joint collaboration of academiaindustry in mobile ultrafiltration water treatment system for flood disaster areas, 14<sup>th</sup> Association of Pacific Rim Universities Doctoral Students Conference, 23<sup>rd</sup> – 26<sup>th</sup> November 2015, Zhejiang University, China

- Chun Ming Chew, M.K. Aroua, M.A. Hussain, Ultrafiltration membrane systems for industrial-scale and portable scale drinking water supply, 10<sup>th</sup> Asia-Oceania Top University League on Engineering Student Conference, 1<sup>st</sup> – 3<sup>rd</sup> November 2015, Nanyang Technological University, Singapore
- 4. **Chun Ming Chew**, M.K. Aroua, M.A. Hussain, Utilizing results from laboratory and pilot plant for the design of industrial-scale ultrafiltration membrane water treatment plant, 10<sup>th</sup> Asia Pacific Conference on Sustainable Energy & Environmental Technologies, 2<sup>nd</sup> 5<sup>th</sup> July 2015, University of Seoul, Korea
- Chun Ming Chew, M.K. Aroua, M.A. Hussain, Comparison between bench-scale, pilot-scale and industrial-scale studies of ultrafiltration systems performance, 27<sup>th</sup> Symposium of Malaysian Chemical Engineers and 21<sup>st</sup> Regional Symposium on Chemical Engineering, 28<sup>th</sup> – 31<sup>st</sup> Oct 2014, Taylor's University, Malaysia
- 6. **Chun Ming Chew**, M.K. Aroua, M.A. Hussain, Factors affecting operations of ultra-filtration systems in industrial-scaled drinking water plants, 4<sup>th</sup> International Congress on Green Process Engineering, 7 10 April 2014, Sevilla, Spain