Faculty of Engineering

Modelling and Investigating the Impact of Process Control Devices on the Ultrafiltration Membrane Performance

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Modelling and Investigating the Impact of Process Control Devices on the Ultrafiltration Membrane Performance

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgement has been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

……

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DEDICATION

This thesis is a symbol of appreciation to people who help the author to complete the project.

(Supervisor, Family and Friends)

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ABSTRACT

The current research aims to address the problem of Ultrafiltration Membrane's (UFM) low productivity in producing clean water that affect the water demand. The novelty of this research is of increasing productivity at a minimum energy consumption performance at optimum clean water production by UFM in association process of control devices (PCD). Experimental research has conducted with UFM, PCD, feed water pump and clean water storage tank. The experimental runs were estimated by central composite design (CCD) and optimization was determined by design of experiments (DOE). The experiment was divided into the three main steps. Step one assesses the effect of the PCD on permeate flux [$m^3(sqm)^{-1}$] by operating the system without, and then with PCD. Step two evaluates the impact of PCD on energy consumption rate [$kW(m^3)^{-1}$] using a similar two-phase approach. Step three aims to optimize UFM performance by adjusting and analyzing feed water pressure (bar), energy consumption rate [$kW(m^3)^{-1}$] and permeate flux [$m^3(sqm)^{-1}$]. The experimental findings demonstrated that PCD devices have significantly impacted on saving 31.6% in permeate flux wastage at a P-value < 0.05. Additionally, the PCD has significantly (at P-value < 0.05) contributed to produce clean water at energy consumption rate 0.43 $kW(m^3)^{-1}$.The optimum performance (at P-value < 0.05) of UFM in association with PCD was 0.68 m^3 $(sqm)^{-1}$ clean water production per square meter of membrane surface area at 1.5 bar optimum pressure and 0.42$kW(m^3)^{-1}$ energy consumption rate. The R^2 statistic of the regression was 0.8993, which is good fit of the regression, meaning is the output is 89.93% associated with inputs. The research findings have a few implications in contributing to achieve higher productivity in clean water production by UFM, which will obviously reduce the water crisis, water production cost. This finding would be a reference for policy makers and government agencies involved in clean water sustainability (SDG 6). In conclusion, this

research has provided valuable insights into the impact of process control devices and UFM on optimization of clean water at a minimum energy consumption rate. The performance optimization of UFM by the process control devices are the Novelty of this work. indeed, this study suggests for further research in this field for developing a robust model.

Keywords: UFM, process control devices, permeate flux, energy consumption, performance, optimum, modelling

Menentukan Kesan Peranti Kawalan Proses Terhadap Prestasi Membran Ultrafilter Dalam Pengeluaran Air Bersih

ABSTRAK

Penyelidikan semasa bertujuan untuk menangani masalah produktiviti rendah membran Ultrafiltrasi dalam pengeluaran air bersih yang mempengaruhi permintaan air. "Novelty" penyelidikan ini adalah untuk meningkatkan produktiviti pada prestasi penggunaan tenaga minimum pada pengeluaran air bersih optimum oleh membran Ultrafiltrasi (UFM) dalam proses peranti kawalan (PCD). Penyelidikan eksperimen telah dijalankan dengan UFM, PCD, pam air suapan dan tangki simpanan air bersih. Rancangan eksperimen ini telah dianggarkan oleh reka bentuk komposit pusat (CCD) dan pengoptimuman telah ditentukan oleh reka bentuk eksperimen (DOE). Eksperimen ini dibahagikan kepada tiga langkah utama. Langkah pertama menilai kesan PCD pada fluks air bersih [$m^3(sqm)^{-1}$] dengan mengoperasikan sistem tanpa dan kemudian dengan PCD. Langkah kedua menilai kesan PCD pada kadar penggunaan tenaga [$kW(m^3)^{-1}$] menggunakan pendekatan dua fasa yang serupa. Langkah ketiga bertujuan untuk mengoptimumkan prestasi UFM dengan melaraskan dan menganalisis tekanan air suapan (bar), kadar penggunaan tenaga [$kW(m^3)^{-1}$] dan fluks [$m^3(sqm)^{-1}$]. Penemuan eksperimen menunjukkan bahawa peranti PCD mempunyai kesan yang ketara dalam menjimatkan 31.6% fluks pada nilai $P < 0.05$. Selain itu, PCD telah menyumbang dengan ketara (pada nilai $P < 0.05$) dalam pengeluaran air bersih pada kadar penggunaan tenaga 0.43 $kW(m^3)^{-1}$. Prestasi optimum (pada nilai $P < 0.05$) UFM yang berkaitan dengan PCD adalah 0.68 $m^3(sqm)^{-1}$ pengeluaran air bersih per meter persegi kawasan permukaan membran pada tekanan optimum 1.5 bar dan kadar penggunaan tenaga 0.42 $kW(m^3)^{-1}$. Statistik R^2 regresi adalah 0.8993, yang menunjukkan kesesuaian yang baik bagi regresi, bermakna output adalah 89.93% berkaitan dengan input.

Penemuan penyelidikan ini mempunyai beberapa implikasi dalam menyumbang kepada peningkatan produktiviti dalam pengeluaran air bersih oleh UFM, yang secara jelas akan mengurangkan krisis air, kos pengeluaran air. Penemuan ini akan menjadi rujukan untuk pembuat dasar dan agensi kerajaan yang terlibat dalam kelestarian air bersih (SDG 6). Kesimpulannya, penyelidikan ini telah memberikan pandangan berharga tentang kesan peranti kawalan proses dan UFM terhadap pengoptimuman air bersih pada kadar penggunaan tenaga minimum. Pengoptimuman prestasi UFM oleh peranti kawalan proses adalah kebaruan kerja ini. Malah, kajian ini mencadangkan penyelidikan lanjut dalam bidang ini untuk membangunkan model yang kukuh.

Kata kunci: *Membran ultrafilter, peranti kawalan proses, fluks, penggunaan tenaga, prestasi, optimum, pemodelan*

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LIST OF ABBREVIATIONS

AFM	Analogue Flow Meter
CAC	Command and Control
CCD	Central Composite Design
CLC	Close Loop Control
CMA	Critical Material Attributes
CMF	Crossflow Membrane Filtration
CP	Concentration Polarization
CPP	Critical Process Parameters
CQA	Critical Quality Attributes
CU	Capacity Utilization
CUF	Capacity Utilization Factor
CV	Control Valve
DCS	Distributed Control System
DOE	Design of Experiments
ECMT	Energy Consumption and Monitoring Technology
HMI	Human Machine Interface
I&C	Instruments and Control
RSM	Response Surface Methodology
SDG	Sustainable Development Goals
J	Permeate Flux
MF	Microfiltration
MFM	Microfiltration Membrane

MTDP	Maximum Target Desired Profile
NDP	Net Driving Pressure
NFM	Nanofiltration Membrane
NRW	Non-Revenue Water
OP	Osmotic Pressure
Pa	Pascal
PG	Pressure Gauge
pH	Potential of Hydrogen
PID	Proportional, Integral and Derivative
PLC	Programmable Logic Controller
RM	Ringgit Malaysia
RO	Reverses Osmosis
SS	Suspended Solids
TMP	Transmembrane Pressure
TDS	Total Dissolve Solids
TSS	Total Suspended Solids
UF	Ultrafiltration
UFM	Ultrafiltration membrane
TMP	Transmembrane Pressure
VFD	Variable Frequency Drive
WWTP	Wastewater Treatment Plant

CHAPTER 1

INTRODUCTION

1.1 Introduction

Chapter 1.0 describes the objective of this study, which is focused on determining the impact of process control devices on the performance of UFM in clean water production. This research is an experimental work, which aims to evaluate the process control devices on the productivity in permeate flux production by UFM, to demine the impact of process control devices on the energy consumption in permeate flux production, and finally optimizing the performance of UFM with respect to permeate flux and energy consumption. The chapter is structured as follows: Section 1.2 provides an overview of the research background. Sections 1.3 and 1.3.1 present the problem statement and research questions, respectively. The research objective is explicitly stated in Section 1.4, while the scope of the research is specified in Section 1.4.1. Sections 1.5 and 1.6 are dedicated to outlining the hypotheses and highlighting the novelty of this research. The structure of the thesis is elucidated in Section 1.7, and a summary of the chapter is presented in Section 1.8.

1.2 Background of Research

This research endeavors to confront the prevalent challenge of subpar performance in clean water production, a significant obstacle hindering the attainment of a sustainable and reliable clean water supply for safeguarding public health. To fulfill the research objective specifically, enhancing the efficiency of the UFM system process control devices have been employed. These devices play a pivotal role in mitigating water and energy wastage while concurrently optimizing the overall performance of the UFM.

Water plays an indispensable role in meeting the daily needs of all living organisms on this planet in which its absence would inevitably lead to the extinction of life (Ross, 2022). Water sources are leveraged for the socio-economic development (Mannina et al., 2022). Sarawak is blessed with vast natural water resources, primarily sourced from rivers and drains. In regards water supply, it should not be a problem, but the opposite seems to be the case with the water crisis being reported every year, affecting thousands of people who endure water shortages (Abdul Rahman et al., 2023). Contrary to expectations and standard measurements, this state should not be experiencing a water crisis (Elena et al., 2023).

There are 222 water-stressed areas identified by the Sarawak State Authorities (Borneo Post Online, 2018). The clean water crisis in Sarawak has been attributed to inadequate water management, water pollution, and inefficiencies in water production. The primary sources of pollution include industrial wastes, household garbage dumps, palm oil mill effluent, oil and chemical spills, hospital wastes, and sewage dumps. These factors collectively exert a substantial impact on the production of clean water in the region (Zainal Abidin, 2015).

Various incidents of water contamination have also been reported as a result of waste disposal from the manufacturing industries which includes palm oil mills, livestock, construction, and oil spills. All these pollutants are affecting the ability of treatment plants to treat polluted water (Dalun & Abdullah, 2021). A few studies on clean water supply constraint issues demonstrated that the poor productivity of existing water treatment plants is also responsible for the water crisis in the state (Rahman et al., 2021).

Several factors contributing to the shortage in clean water supply have been identified. The increased demand for water, driven by population growth, rapid expansion

of unregulated areas, and industrialization, stands out as a primary cause. Firstly, the escalation of industrialization and the expansion of irrigated agriculture further intensify the strain on water resources. Additionally, a significant factor exacerbating the shortage is the slower growth rate of clean water production in comparison to the escalating demand for water.

While Sarawak is endowed with abundant natural water resources, the data reveals a significant impact on numerous communities across different regions owing to a shortage of clean water. This issue can be attributed to various constraints, such as the absence of suitable technology, inefficiencies in water resource development, and the inability to harness natural water sources due to pollution (Subramaniam et al., 2020; Chew et al., 2021).

Advanced filtering techniques called UFM are used to remove dissolved molecules, bacteria, and particles from liquids, usually water. These membranes are efficient at eliminating pollutants like bacteria, viruses, colloids, and suspended particles because their pore diameters fall between 0.01 and 0.1 micrometres. UFM have extensive application in diverse industries such as biotechnology, food and beverage processing, pharmaceuticals, and water and wastewater treatment. Because of their many advantages—including high filtration efficiency, low energy consumption, and low-pressure operation—they are a well-liked option for applications needing high-purity water (Ma, B., et al., 2019).

Given this background, the central question emerges: "***Can the performance and energy consumption rates reach their optimum levels through the use of ultra-filter membrane***, *thereby achieving the research objectives*?" This study is meticulously crafted to provide a comprehensive answer to this inquiry. To achieve this goal, the research combines a comprehensive literature review with an experimental investigation employing

the necessary process control system. The aim is to develop a sustainable solution that effectively addresses the issue of water scarcity.

1.3 Problem Statement

The global water crisis is a daily headline, and in Sarawak, the provision of clean water has emerged as a pressing state concern (Abdul Rahman et al., 2023). The current scenario of clean water demand and supply in Sarawak demonstrates that, certainly, some essential elements are missing in the clean water production domain, and obviously, the lack of process engineering design and the optimum performance of the plant are underutilised.

There are various reasons for water shortages, such as lack of proper operation and maintenance, inappropriate technology with improper technology application in place, inefficiency in plant machinery, non-revenue water (NRW), underutilization of installed water treatment plant machinery, and poor productivity in water production (Anjum et al., 2019). Numerous incidents of water contamination have been reported, primarily attributed to waste disposal from various manufacturing industries. These industries include palm oil mills, livestock farming, construction activities, and oil spills. All these pollutants are affecting the ability of water treatment plants to produce required clean water (Mokarram et al, 2020). Most importantly, it has been recognized that traditional process systems are incapable of addressing all the aforementioned issues.

Several studies have highlighted constraints and issues in clean water production. The clean water crisis is, in part, attributed to the suboptimal productivity of plant machinery in clean water production. This inefficiency stems from the reliance on traditional process control systems, inadequate capacity planning during plant design, and a low-capacity utilization factor (Tirkolaee et al., 2020; Li et al., 2021; Rahman et al., 2021). One of the

identified issues is the traditional process control system. This situation prompts a crucial question: "Are process control devices indispensable for enhancing the UFM's performance in generating permeate flux?"

Among all the problems and questions outlined herein, it becomes evident that poor performance in clean water production stands out as a potential issue and a hindrance to achieving the sustainability of a clean water supply. In response to this specific challenge, the current research is dedicated to enhancing the performance of clean water production by incorporating process control devices into the water filtration process. Indeed, the research question and research objectives have been developed to specifically address this identified problem**.** The research question will be answered by the proposed research:

i. What is the effect of process control devices on the productivity [$m^3(sqm)^{-1}$] in permeate flux production?
ii. What is the impact of process control devices on the energy consumption rate [($kW(m^3)^{-1}$] permeate flux) and productivity in permeate flux?
iii. What is the empirical model that could be used to predict optimum level of permeate flux [m3(sqm)-1] with respect to feed pressure (bar) and energy consumption rate (kW(m3)-1]) at the effect of process control devices?

1.4 Research Objectives

The broad objective of this research is to optimize the performance of the UFM in permeate flux yield [$m^3(sqm)^{-1}$] in the respect of the energy consumption rate ([$kW(m^3)^{-1}$]) and feed pressure. To achieve this goal, this research is divided into the three specific objectives:

i. To determine the effect of process control devices on the productivity [$m^3(sqm)^{-1}$] in permeate flux production.

ii. To evaluate the impact of process control devices on energy consumption rate [$kW(m^3)^{-1}$] in permeate flux production performance of UFM.

iii. To optimize the performance of UFM with respect to permeate flux [$m^3(sqm)^{-1}$], feed water pressure(bar) and energy consumption rate [$kW(m^3)^{-1}$].

1.4.1 Scope of Study

The broad objective of this research is to optimize the performance of the UFM in permeate flux yield [$m^3(sqm)^{-1}$] in the respect of the energy consumption rate ([$kW(m^3)^{-1}$]) and feed pressure. The key equipment used for this experiment are UFM, feed water pump, and process control devices (process control devices include VFD and water level sensor at the tank).

The scope of work for objective 1.0 is to evaluate the effect of process control devices on the permeate flux rate [$m^3(sqm)^{-1}$]. To achieve this goal, the UFM plant operates in two phases. In the first phase, the experiment has been conducted with process control devices to produce permeate by UFM. In the second phase, the experiment has been conducted without process control devices to produce permeate by UFM.

The scope of work for objective 2.0 is to evaluate the effect of process control devices on the energy consumption rate [$kW(m^3)^{-1}$]. To achieve this goal, the UFM plant operates in two phases. In the first phase, the experiment has been conducted with process control devices to produce permeate by UFM. In the second phase, the experiment has been conducted without process control devices to produce permeate by UFM.

The scope of work for objective 3.0 is to optimize the performance of UFM with respect to permeate flux [m3(sqm)-1], feed water pressure(bar) and energy consumption rate [kW(m^3) $^{-1}$]. In order to achieve this goal, the UFM plant operates various feed pressure and process control devices to optimize permeate flux [m^3(sqm)$^{-1}$], feed water pressure (bar) and energy consumption rate [kW(m^3)$^{-1}$]. The flow diagram of this research is attached in appendix H.

1.5 Hypothesis of The Research

The null hypothesis and alternative hypothesis tests have been used for conducted the hypothesis test to evaluate the significance of contribution of process control devices to the performance of UFM in permeate flux production [m^3(sqm)$^{-1}$], and energy consumption rate [kW(m^3)$^{-1}$].

1.5.1 Hypothesis Test for Permeate Flux Production

(a) Null Hypothesis Test

Ho: $\mu 1 = \mu 2$ at 95% confidence level at (P-value > 0.05). **(Equation 1.1)**

If P-value of mean difference of permeate flux (ΔQp_F) with and without process control devices is more than 0.05 (P-value > 0.05), it will indicate that the mean of two data sets is almost equal and has no significant difference. This means the process control devices is not required in water filtration (WF) process.

(b) Alternative Hypothesis Test

H_1: $\mu 1 \neq \mu 2$ at 95% confidence level at (P-value $\leq$ 0.05). **(Equation 1.2)**

If P-value of mean difference of ΔQp_F with and without process control devices is less than 0.05 (P-value ≤ 0.05), it will indicate that the mean difference of two data sets is not equal and has significant difference. This means process control devices are required in WF process.

1.5.2 Hypothesis Test for Energy Consumption Rate

(a) Null Hypothesis test

Ho: $\mu 3 = \mu 4$ at 95% confidence level at (P-value > 0.05). **(Equation 1.3)**

If P-value of mean difference of energy consumption rate ΔE with and without process control devices is more than 0.05 (P-value > 0.05), it will indicate that the mean of two data sets is almost equal and has no significant difference. This means the process control devices are not required for energy saving in water filtration (WF) process.

(b) Alternative Hypothesis Test

H_1: $\mu 3 \neq \mu 4$ at 95% confidence level at (P-value ≤ 0.05). **(Equation 1.4)**

If P-value of mean difference in energy consumption rate ΔE with and without process control devices is less than 0.05 (P-value ≤ 0.05), it signifies a significant disparity between the two datasets. This outcome implies that process control devices are essential for achieving energy savings in WF process.

1.5.3 Hypothesis Test for Optimal Performance of UFM

(a) Null Hypothesis test

Ho: $\mu 5 = \mu 6$ at 95% confidence level at (P-value > 0.05). **(Equation 1.5)**

If P-value of mean difference on performance of UFM with and without process control devices are more than 0.05 (P-value > 0.05), it will indicate that the mean of two datasets is almost equal and has no significant difference. This implies that process control devices have no significant contribution on the performance with respect to optimum performance of UFM.

(b) Alternative Hypothesis Test

H_1: $\mu 5 \neq \mu 6$ at 95% confidence level at (P-value $\leq$ 0.05). **(Equation 1.6)**

If P-value of mean difference on performance of UFM with and without process control devices are less than 0.05 (P-value $\leq$ 0.05), it will indicate that the mean difference of two data sets is not equal and has significant difference. This indicates process control devices have significant contribution on the performance with respect to optimum performance of UFM.

1.6 Novelty and Contribution of Research

In general, process control devices such as level sensor and VFD have been commonly used in industry, especially in the water industry. Although the implementation of process control devices has been applied, level sensor and VFD are not fully utilized in optimization of the performance of the ultrafiltration. Therefore, this research introduces a novel approach by demonstrating the significant contribution of process control devices such as level sensors and VFD in enhancing optimum performance, thereby improving resource efficiency, and mitigating the impacts of water scarcity.

1.7 Structure of The Thesis

The structure for this report is presented in **Figure 1.1**.

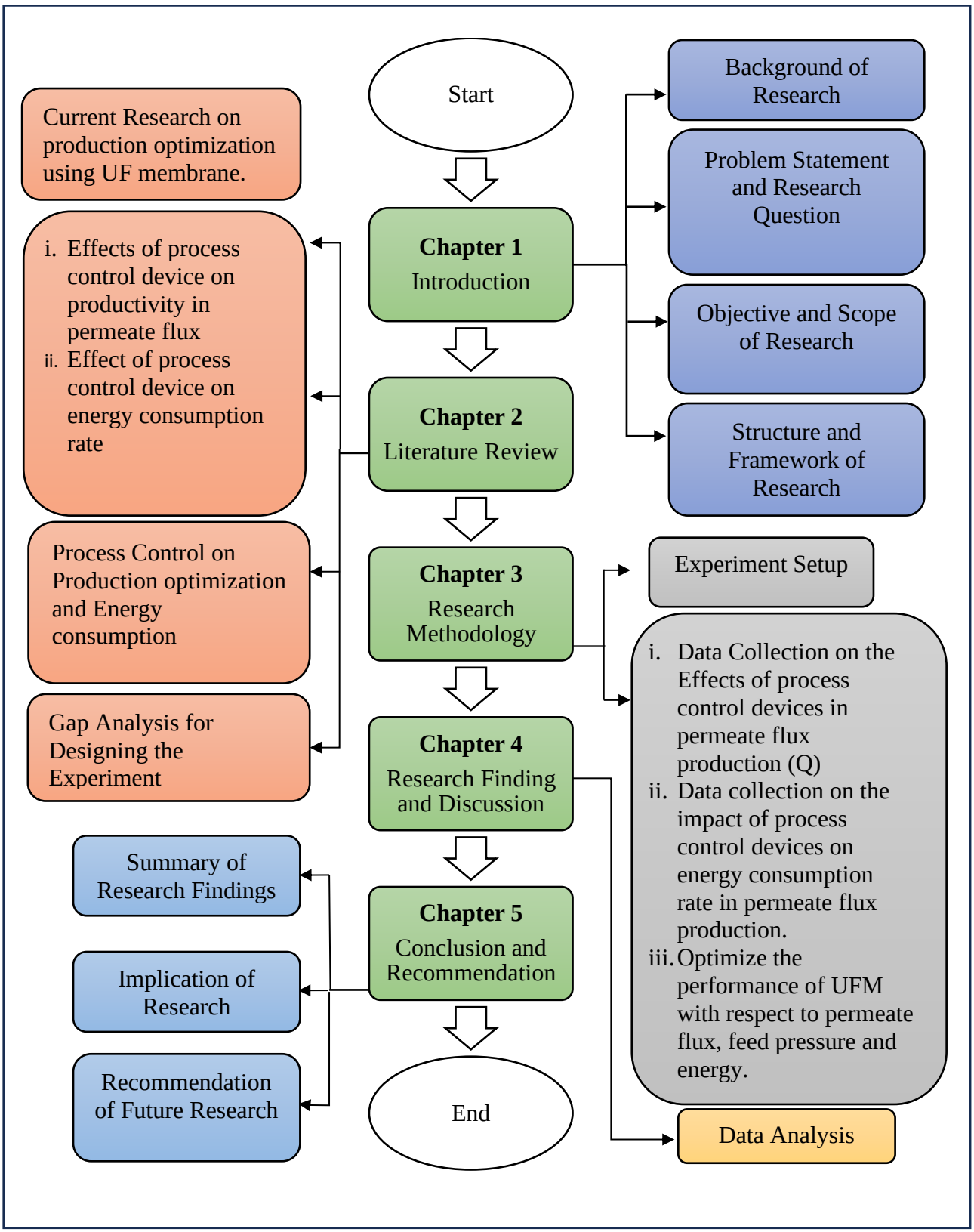


Figure 1. 1: Structure of the Thesis

In order to achieve the study's objectives, the report is organized into five chapters. Chapter 1 serves as a comprehensive introduction to the research, encompassing the study's background, the problem statement, the research question, the research objectives, the scope of study, the research framework, and the overall structure of the report. Chapter 2 encompasses a comprehensive literature review, focusing on current research pertaining to membranes, with a particular emphasis on UFM their optimal performance. This review spans key aspects such as feed pressure, permeate flux, energy conservation, process optimization, and the influence of independent variable parameters on dependent variables. In Chapter 3, the experimental setup, and the procedural details for conducting the experiment are elucidated. This section provides a thorough understanding of how the research was implemented, offering insights into the methodology employed. Moving forward to Chapter 4, this segment is dedicated to the meticulous analysis of data, presentation of output results, and a scenario analysis based on the research findings. Here, a comprehensive examination of the collected data is undertaken, culminating in a detailed exploration of the outcomes and potential scenarios derived from the research. Data is analyzed using Design Expert Software, Version 13, and presented with tables and graphs. Chapter 5 discusses research outcomes, implications, novelty, future research recommendations, limitations, and conclusions. Appendixes provide supporting data and study background, while references and related documents are included for further review.

1.8 Chapter Summary

This research delves into diverse strategies aimed at enhancing the performance of UFMs to attain optimal productivity and energy efficiency in conjunction with process control devices. Additionally, the study evaluates the effectiveness of energy and

productivity concerning permeate flux. Furthermore, it investigates the impact of variables such as feed pressure, optimum productivity, permeate flux, energy consumption, energy efficiency, and permeate flux efficiency.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter aims to elucidate the factors influencing the water productivity, energy consumption and performance of UFMin producing clean water, aligning with the objectives of Sustainable Development Goal 6 (SDG 6). The study focuses on the operational parameters of water filtration plant machinery, particularly those impacting the optimization of overall performance of UFM in producing water productivity.

UFM are categorized into three groups based on their molecular weight cut-off (MWCO), with dead-end flux flow being a key consideration in this classification. Abdullah et al. (2022) emphasize the importance of assessing flux performance in both dead-end and crossflow modes, using convolutional neural networks to optimize these processes. Membrane filtration has garnered attention as an advanced water treatment process due to its ease of operation and low maintenance requirements (Smith & Johnson, 2019; Yogarathinam et al., 2022; Lee, 2023).

The design of a UFM plant requires intermediate engineering expertise to ensure reduced energy consumption and minimal capital investment. However, the widespread adoption of UFM is often hindered by challenges in achieving the desired performance, particularly in terms of clean water production. One significant challenge is membrane fouling, which impairs efficiency and performance. While the broader literature often addresses factors like total suspended solids (TSS) and natural organic materials (NOM) (Lay et al., 2021), this research focuses on optimizing operational parameters and control strategies. These include factors such as plant operating time, cleaning efficiency, and the integration of advanced

process control devices, which are crucial for maintaining high efficiency and consistent water quality in UFM systems (Abdullah et al., 2022; Brover et al., 2022).

The mode of UFM plant operation is crucial for sustainable performance, including factors such as operating time and cleaning efficiency. These factors are closely related to energy consumption, plant maintenance frequency, the life cycle of UFM modules, and water production costs. Optimization of these parameters is essential for achieving the required performance of UFM systems (Brover et al., 2022).

A major highlight of this chapter is the critical role of process control devices in achieving optimal performance of UFM systems. The utilization of devices such as VFDs (VFDs) and level sensors significantly impacts efficiency and energy consumption. VFDs allow for precise control of pump speeds, enabling the system to adjust dynamically to actual flow requirements. This precise control leads to significant energy savings by reducing unnecessary power usage. Level sensors ensure the maintenance of optimal water levels, which is crucial for consistent feed pressure and membrane protection, thereby preventing damage and extending membrane life.

By integrating these advanced process control devices, UFM systems can achieve enhanced permeate flux and improved energy efficiency, resulting in lower operational costs and a more sustainable water treatment process. The optimized use of these technologies not only enhances system performance but also contributes to the overall sustainability and economic viability of water filtration plants.

In conclusion, this chapter explores the optimal operational parameters and control strategies for UFM systems, emphasizing the substantial benefits brought about by the utilization of process control devices. These devices are key to overcoming performance

challenges, improving efficiency, and achieving sustainable performance in clean water production, all while minimizing energy consumption and operational costs

2.2 Definition and Classification of Membrane

This section provides an overview of the literature relevant to the objectives of the present research. It encompasses a comprehensive literature review that delves into the definition of membranes and their classifications. The fundamental principle governing membranes is rooted in pressure-driven mechanisms. There are four types of membranes which are (i) Microfiltration Membrane (MFM), (ii) UFM (UFM), (iii) Nanofiltration Membrane (NFM), (iv) Reverse Osmosis Membrane (ROM). Nevertheless, this master's thesis employs UFM (UFM), a semipermeable membrane that functions as a barrier regulating the passage of particles and bacteria. As the transition occurs from microfiltration to reverse osmosis, the retained particle sizes decrease, necessitating a reduction in membrane pore sizes. Consequently, membrane resistance intensifies, demanding an increased applied driving pressure to achieve optimal efficiency without compromising permeate flux. Figure 2.1 shows a pollutant separation range where the membrane pore size of each membrane is classified.

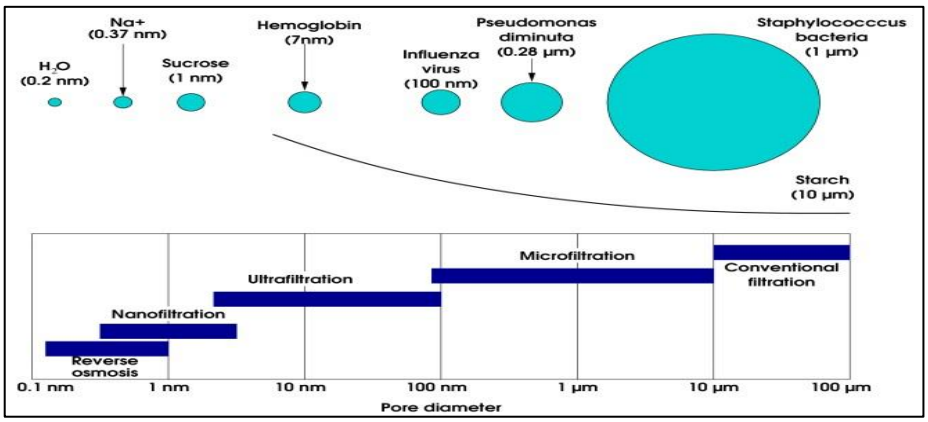


Figure 2. 1: Pore Size Diameter of Each Membrane Classification (Anis et al., 2019)

A membrane serves as a barrier between two distinct mediums, functioning to selectively reject water impurities. These impurities encompass suspended solids, dissolved solids, and bacteria (Liu et al., 2021). The impurity separates mechanically by size exclusion such as molecular sieve (Gössi et al., 2020). The membrane's separation behavior is dictated by its top layer, with the porous layer beneath serving as a supportive element. This supporting layer plays a crucial role in maintaining the mechanical stability of the membrane while simultaneously offering low resistance to permeate flow (Ji et al., 2021).

2.2.1 Dead End UFM

The dead end serves as the fundamental configuration for membrane filtration. This approach is frequently employed in both Microfiltration (MFM) and Ultrafiltration (UFM) processes, specifically for clarification and microbial reduction purposes when the incoming feed is relatively clean. In this method, the flow directly moves toward the membrane, leading to the accumulation of solutes and particles. However, this accumulation can reach levels that are both severe and impractical (Lin et al., 2022).

In dead end membrane, the feed water is force through the membrane surface. The feed water will flow vertically towards the membrane surface and will pass through the membrane outlet port. The flow has two parts. One is product water and the other is concentrates. Due to this factor, the concentration accumulates on the membrane surface, and it creates a higher resistance for the water flow through the membrane. This will lead to form fouling and decrease the water productivity. The dead-end membrane is commonly used in microfiltration (MF) for clarification and sterilization, where the feed is relatively clean (Han et al., 2021). Figure 2.2 demonstrates that permeating flux is reducing with

operating time and membrane resistance (R_M). In R_C is referred to as in cake layer, and J referred to as in permeate flux.

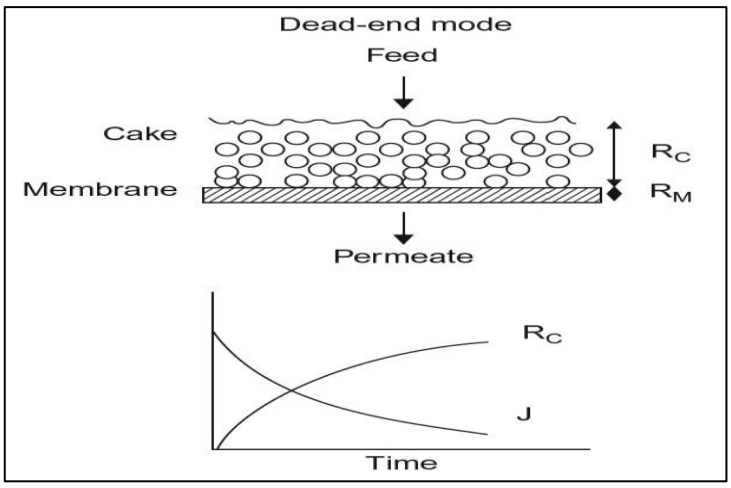


Figure 2. 2: Dead End Filtration Mode, the effects on the permeate flux and the formation of the layer cake (Han et al., 2021)

2.2.2 Cross Flow UFM

In crossflow membrane filtration (CMF), the concentrate flow and permeate flow intersect at right angles. CMF is alternatively referred to as tangential flow filtration. This tangential flow mode effectively removes accumulated rejected solutes and particles from the membrane surface (Gul et al., 2021). In CMF, the formation of layer cake in membrane surface is lower than dead end MF. The performance of CMF in permeate production is also

higher than dead end Microfiltration (Chew et al., 2020). The operating behavior of CMF is presented in Figure 2.3.

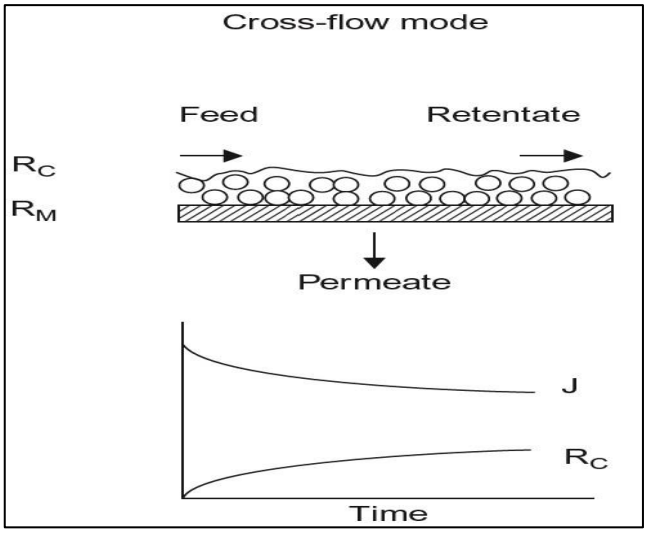


Figure 2. 3: Cross Flow Filtration Mode, the effects on the permeate flux and the formation of the layer cake

Figure 2.3 demonstrates the effect of cross flow on the permeate flux performance. The flux (J) is slightly decreasing when the cake layer (R_c) build up. In the long run of operations, with proper monitoring and maintenance, the cake can be removed to restore membrane performance. CMF is more reliable than dead end MF. Its lifecycle time is also higher. In addition, this will decrease the operational expenditure cost (OPEX).

2.3 Permeate Flux of UFM

The permeate flux (J) can be expressed in below Equation 2.1. It is for measuring the material passing rate through a unit area of membrane per unit time (Li et al., 2023). The transport relationship of the membrane processes operated by the pressure gradient is as follows (Xu et al., 2023).

$$J = K\frac{\Delta P}{t} \qquad \textbf{(Equation 2.1)}$$

Here, J is the permeate flux, $\Delta P\ is$ the pressure difference across the membrane, "t" is the membrane thickness, K is the efficiency factor of UFM in which Halanur Mruthunjayappa et al. (2024) also used a similar model for measuring the performance of UFM.

2.4 Feed Pressure in Producing Permeate Flux from UFM

The feed pressure serves as the primary driving force for solid separation from liquid. The pressure necessary to traverse a membrane is referred to as transmembrane pressure (TMP). TMP is specifically defined as the pressure gradient across the membrane, calculated as the average feed pressure minus the permeate pressure.

Typically, the feed pressure is measured at the membrane module's initial point. However, it is important to note that this pressure does not equate to the average feed pressure. Generally, an elevation in transmembrane pressure corresponds to an increased flux across the membrane. The transmembrane pressure (TMP) is defined by Sreedhar et al. (2023). For crossflow mode of operation can be expressed in Equation 2.2.

$$TMP = \frac{P_f + P_c}{2} - P_p \qquad \textbf{(Equation 2.2)}$$

Where *TMP* is Transmembrane pressure (kPa [psi]),$\boldsymbol{P_p}$ is permeate pressure (kPa [psi]), $\boldsymbol{P_f}$ is feed pressure and (kPa [psi]), $\boldsymbol{P_c}$ is concentrate pressure (kPa [psi]). For the direct feed mode of operation, Equation 2.3 can be used for measuring the *TMP*. It should be noted that with MF/UF, the feed pressure and concentrate pressure are equal.

$$TMP = P_{f-} P_p \qquad \textbf{(Equation 2.3)}$$

2.5 Energy Consumption Rate in Permeate Flux from UFM

The energy consumption rate in producing clean water [kWh $(m^3)^{-1}$] was used to evaluate the performance of UFM. Studies conducted by Li et al. (2022) and Avilés et al. (2020) undertook a pilot study to evaluate the performance of UFM with energy consumption concerning permeate flux [kWh$(m^3)^{-1}$]. Equation 2.4 can use for measuring the energy consumption rate of a UFM in water production.

$$P\ (\frac{kW}{m^3}) = \frac{QP}{\eta_{pump}} \qquad \textbf{(Equation 2.4)}$$

Where P is the power used by pumps and Q ($m^3 h^{-1}$) is the feed flow rate passing through the membrane at a pressure P in the bar. A series of research and development (R&D) activities was conducted to optimize the energy consumption performance [kWh $(m^3\text{-water})^{-1}$] in clean water production using UFMby reducing membrane resistance transmembrane pressure (TMP). The research findings demonstrate that the energy consumption rate in UFM is lower among the membrane family (Upadhyay et al., 2023; Kumar et al., 2023). Additionally, the UFM system is recognised as an economical, sustainable, and environmentally friendly water treatment process due to less energy consumption rate (Richards, 2022). A review in this section concludes that efficiency, productivity, and energy consumption rate per unit of water production are the indicators used to measure the performance of UFM.

2.6 Process Control Devices in Performance Optimization of UFM

The integration of process control systems into ultrafiltration technology is a significant development, considering that UF membranes constitute a well-established method of separation technology employed in various industrial processes globally. Generally, UF membranes possess the capability to purify, concentrate, and fractionate a

diverse range of macromolecules and proteins by utilizing a physical membrane barrier. This mechanism ensures highly consistent rejection rates and optimal flux performance (Schuster & Sleytr, 2021).

In industrial processes and wastewater treatment, optimizing output holds a crucial significance, especially in the context of oil removal. The imperative to adhere to stringent discharge regulations and address escalating manufacturing costs has intensified the need for efficient oil removal from various industrial wastewaters and streams. Ultrafiltration, capable of rejecting particulates, bacteria, protein, and polysaccharides, emerges as a valuable tool. When combined with other technologies, ultrafiltration proves effective in reducing contaminant loads within industrial wastewater effluent.

Qiao et al. (2023) conducted an experiment with the UFM plant to develop an energy consumption model. Findings demonstrated that UFM required energy for feed water pump operations for producing clean water and to operate backwash water supply pumps. It was also reported that the energy consumption of UFM depends on the efficiency of the feed water treatment plant and maintenance of the UFM (Avilés et al., 2020; Li et al., 2022). It was reported that water pre-treatment by utilizing macro and microfiltration for removing TSS, NOM, BOD, and COD from water stream and discovered that rate of cake layer formation on membrane reduced significantly with energy consumption rate 1.0 $kWh(m^3)^{-1}$ (Pé et al., 2012).

2.6.1 Variable Frequency Drive (VFD)

Figure 2.4 shows one the VFD. It is one of an electronic devices used to control the speed and torque by varying the frequency. It is widely used in industrial and commercial application due to their efficiency and performance. VFD is one of the process control devices

or instruments to control the essential applications like water supply systems, where it compensates for fluctuations in demand and elevation, ensuring consistent pressure. An optimal control enabling precise control over the output (dependent variable), which directly impacts energy efficiency and optimum operational performance (Liang and Liao, 2022).

VFD can significantly reduce energy consumption by adjusting the input parameter to match the system requirements. The energy savings are particularly substantial in pumping applications. One of the applications in HVAC system, it is aimed to help convey the entities to have the holistic approach while incorporating energy efficiency measures. An effective use of VFDs as such chillers and colling tower operation improves the performance and coefficient of the performance increase. (Jiang. 2020).

Figure 2. 4: Variable Frequency Drive (VFD)

2.6.2 Level Sensor (Floating Type)

Figure 2. 5: Level Sensor Floating Type

Float level sensors as shown in Figure 2.5 are commonly used to detect liquid levels in a variety of industries, including water treatment, chemical processing, food and beverage, oil and gas, and pharmaceuticals. These sensors work, in which a float rises and falls with the liquid level, turning this movement into a discrete signal for monitoring and control. Float level sensors are based on a buoyant float that moves with the liquid level. This movement is turned into an electrical signal that allows for continuous or point-level measurements (Kumar et al., 2021).

Continuous Float Level Sensors: Magnetic floats are used in conjunction with sensor devices such as magneto strictive wires, reed switches, or resistance tapes to give real-time measurement.

Point Float Level Sensors: Also known as float switches, these detect the presence or absence of liquid at certain levels by activating reed switches via the float's magnetic field.

2.7 Measuring the Performance of UFM

The UFM is a low-pressure driven system extensively applied in water treatment to produce potable water, cooling water for power plants, and process water for the food and chemical industries. Historically, this membrane has been conventionally positioned at the secondary and tertiary levels within the water treatment process (Guo, 2020; Shahidul & Lee, 2014). Several indicators were used for measuring the performance of UFM including permeate flux rate, efficiency in separating TSS and pollutant from feed water, energy consumption rate [kW$(m^3)^{-1}$] for water production, and productivity in clean water production (Jamalinezhad et al., 2020; Rajindar & Singh, 2015). The performance of UFM depends on some potential factors. These factors are osmotic pressure relating to the membrane fouling (Kammakakam & Lai, 2023), which are (a) complete pore blocking, (b) internal pore blocking, (c) partial pore blocking, (d) cake filtration, (e) feed pressure (Bar), (f) energy consumption rate (kW$(m^3)^{-1}$), (g) permeate flux [m^3(sqm)-1], (h) membrane cleaning frequency, (i) performance of process control devices, (j) degree of carbon emission, and (k) pollutant separation efficiency.

2.8 Theoretical Framework Relating to Performance of UFM in Clean Water Production

The energy consumption rate [kW$(m^3)^{-1}$] of UFM depends on volume of water produced (m^3) and duration (time) of water production. The average energy consumption rate (*Eavr)* over time can be estimated from Equation 2.5.

$$Eavr = \frac{\sum_j^n E_j}{n} \quad kW.(m^3)^{-1} \qquad \textbf{(Equation 2.5)}$$

Here, E_j is energy consumption rate of UFM's feed water pump, n is the number of repeat the same amount of water production from a UFM plant (n>1), Variable j = *1,2,3.....8* and (*Eave)* is the average energy consumption, and *(Ø)* is an experimental runs. This can be referred to Equation 2.6.

$$Eave = \frac{\sum_{i}^{Ø} E_{avri}}{Ø} kW.\ (m^3)^{-1} \qquad \textbf{(Equation 2.6)}$$

Here, *'Ø'* is number of the total experimental runs, and its value is more than one (Ø>1). The range of variable '*i*' is, *i= 1,2,3 ...Ø.* The total water outputs (Qt) of UFM's pump can be estimated from Equation 2.7.

$$Qt = QxØ\ m^3 \qquad \textbf{(Equation 2.7)}$$

Total energy consumption (E_t) during an identified quantity of water production (Qm^3) can estimate from Equation 2.8.

$$Et = Eave\ kW.\ (m^3)^{-1} \times Qt\ m^3 = Eave \times Qt\ kW \qquad \textbf{(Equation 2.8)}$$

Here, Q_t is total water output from an identified experimental run during UFM's plant operation. The required water production and supply rate [Q $m^3(hr)^{-1}$] can be estimated from Equation 2.9 as in Water Treatment Plant Design (Zhang et al., 2023).

$$Qt = \frac{\beta \times Water\ demand,(Qcons)}{No\ of\ experiment\ runs,(Ø)} \qquad \textbf{(Equation 2.9)}$$

Here, β is safety factor of water demand, β=1.1. Pump speed (RPM) and pump output (Qt) can estimate from Equation 2.10 in recent study of Water Treatment Plant Units (Aziz and Mustafa, 2021)

$$\frac{Qt2}{Qt1} = \frac{N2}{N1} \quad \textbf{(Equation 2.10)}$$

Qt1 : Design capacity of flow rate input to UFM (Without PCD)

Qt2 : Design capacity of flow rate at zero wastage input to UFM (With PCD)

N1 : Design capacity of pump speed (Without PCD)

N2 : Design capacity of pump speed at zero wastage (With PCD)

The impact of process control device on energy consumption (ΔE) can be estimated from Equation 2.11.

$$\Delta E = E_t(oc) - E_t(wc) \quad \textbf{(Equation 2.11)}$$

Here, Et(wc) is energy consumption of UFM's pump when operating with the process control devices and E_t(oc) is the energy consumption of UFM's pump when operating without the process control devices. The impact in percentage can be measured from Equation 2.12.

$$\Delta E\ (\%) = \frac{E_t(\mathrm{oc}) - E_t(\mathrm{wc})}{E_t(oc)} 100 \quad \textbf{(Equation 2.12)}$$

The efficiency of UFM can be estimated from Equation 2.13.

$$\eta = \frac{water\ demand\ by\ end\ users}{Clean\ water\ produce\ by\ UFM} 100 = \frac{Qcons\ m^3}{Qout\ m^3} 100 \quad \textbf{(Equation 2.13)}$$

Here, η is the efficiency of UFM in producing clean water. The impact can be measured by estimating Equation 2.14.

$$\Delta \eta = [\eta(oc) - \eta(wc)] \quad \textbf{(Equation 2.14)}$$

In this context, $\eta(oc)$ represents the efficiency of the UFMin generating clean water during operation without the use of process control devices. Conversely, $\eta(wc)$ signifies the efficiency of the UFM in producing clean water when equipped with the process control devices. Equations 2.13 to 2.14 can be used for analyzing experimental data for achieving research objectives.

2.9 Factors Affecting the Performance of UFM

2.9.1 Membrane Pore Size Affect Performance of UFM

The pore size of UFM the diameter of impurities are pivotal factors that significantly impact UFM performance. Ranging between 0.004 to 0.45 μm, the pore size of UFM plays a crucial role. A study performed by Zirehpour et al. (2016) highlighted the effectiveness of UFM in removing various impurities such as TSS, NOM, and bacteria from feed water streams. UFM operates as a porous media, employing molecular sieving to separate impurities from water. To achieve the required water quality, it is imperative that the pore size of UFM is smaller than the diameter (d) of the impurities. Simultaneously, the operating parameters of UFM serve as key evaluative metrics for performance. These parameters include the duration of plant operations, feed water pressure, membrane backwash frequency, feed water flow rate, and the utilization of process control devices. Together, these factors contribute to the overall efficiency and effectiveness of UFM in water treatment processes.

2.9.2 Effect of Pre-Treatment Efficiency on the Performance of UFM

Several researchers have found a positive correlation between the efficiency of feed water pre-treatment and the performance of UFM systems. According to reports, an effective feed water pre-treatment is essential to prevent the formation of cake layers, which could otherwise damage membrane modules and lead to increased energy consumption (Klomaas et al., 2004; Mozia, 2005). Studies conducted by Ladouceur et al. (2023) and Poirier et al. (2023) investigated the effects of feed water pre-treatment on the fouling of UFM. The research findings by Huang et al. (2024) found out that if the coagulation method proves ineffective in removing NOM from the feed water, it necessitates the installation of additional pre-treatment measures. In this regard, a few researchers recommended installing series of pre-treatment such as sedimentation, aeration, media filtration, and microfiltration (Ahmed et al., 2021; Peter-Varbanets et al., 2009).

2.9.3 Effect of Membrane Cleaning on the UFM Performance

The membrane cleaning aims to restore adequate permeate flux. A study conducted by Alhussaini et al. (2023) revealed that the backwash period has a significant (P-value<0.05) effect on the removal of the cake layer accumulated on the membrane surface. In this aspect, Tran et al. (2023) found that membrane-cleaning by backwash water and chemicals have a significant effect on reducing the cake layer that formed due to water-borne bacteria bio-film and NOM. Wang et al. (2016) and Levvitsky et al. (2012) stated that membrane cleaning is a process whereby deposited substances remove from the membrane. The UFM cleaning can be performed biologically, chemically, and physically. Tang et al. (2022) pointed out that the effective ways to clean UFM are backwash (BW) with clean water and chemically enhanced

backwash (CEB). The effect of membrane cleaning by BW and CEB is presented in **Error! Reference source not found.**2.6 (Shahidul & Michael, 2022).

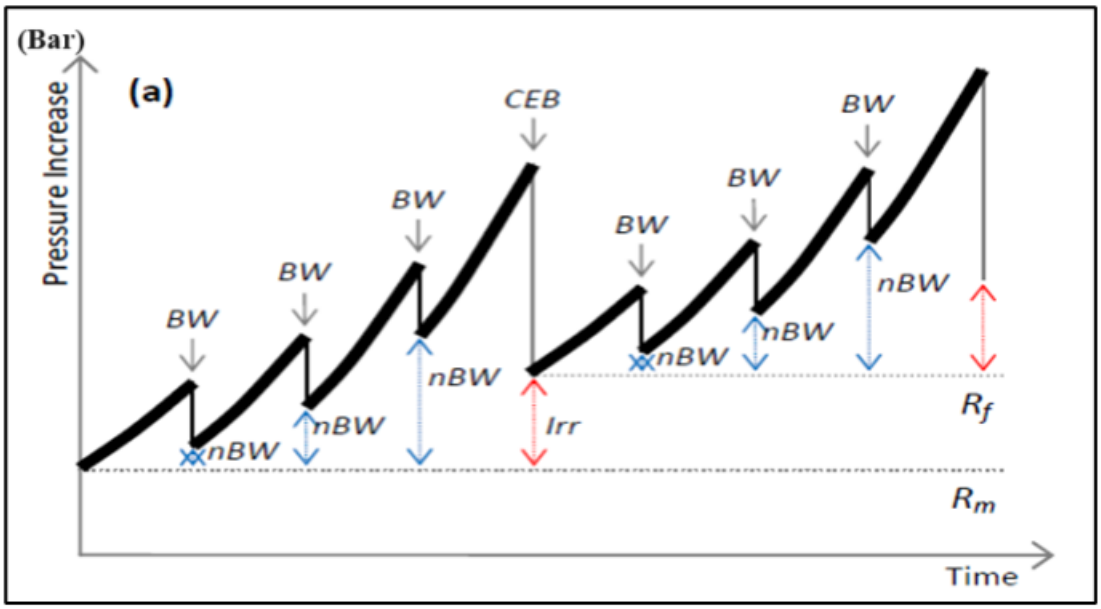


Figure 2. 6: Effect of backwash on UFM cleaning Performance (Shahidul & Michael, 2022)

Irr : Irreversible
R_m : Membrane resistance
R_f : Retention factor

Figure 2.6 demonstrates the effect of backwash (BW) and non-backwash (nBW) by water and chemically enhanced backwash (CEB), which indicates that the impact of CEB in membrane cleaning is much higher than that of BW.

2.9.4 Effect of Feed Water Pressure on Water Production Performance of UFM

A few reports demonstrated that feed water pressure is a factor that affects the performance of UFM. A study performed by Vishali & Kavitha (2021) observed that feed water pressure influences the water production performance of UFM. **Error! Reference source not found.**2.7 presents the effect of feed pressure on the permeate flux of the UFM.

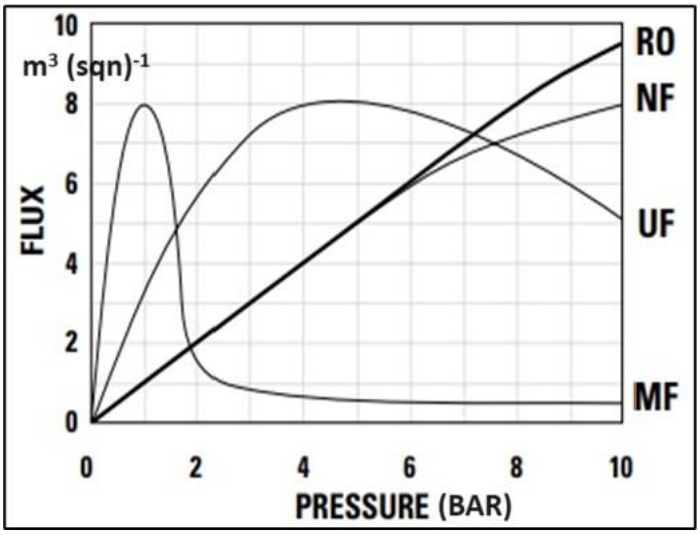


Figure 2. 7: The effect of feed pressure on permeate flux of UFM

Figure 2.7 demonstrates that permeate flux increases with feed water pressure, and after attaining optimum value, permeate flux starts to reduce. In some similar studies, Tansel et al. (2017) revealed that permeate flux increases with feed pressure up to the optimum level. Research reports also demonstrated that the effect of feed water pressure on TDS separation by UFM is insignificant (P-value > 0.05). However, the TSS separation appeared to be significantly higher (P-value ≤ 0.05) (Wahab et al., 2012). Moreover, it was disclosed by Azmi et al. (2013) that the permeate flux of UFM increased to an optimum level with an identified certain feed pressure. These findings suggested that feed pressure affects the performance of UFM.

2.9.5 Effect of Operating Time on Permeate Flux of UFM

Wang et al. (2021) discovered that the operating hour of UFM has an effect on permeate flux, cake layer thickness, TMP, and energy consumption. Russell and Kumar (2017) have conducted experiments with UFM. **Error! Reference source not found.**2.8 shows that the permeate flux decreases with operating time (≥30 minutes) of UFM.

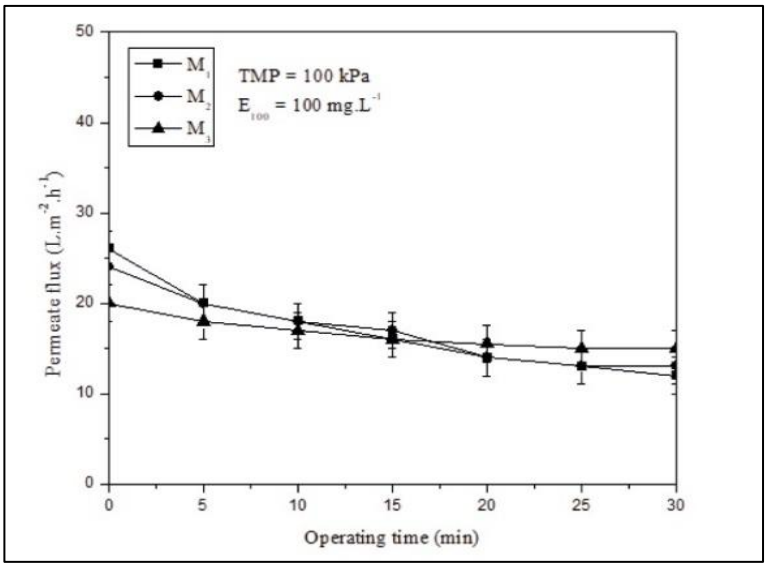


Figure 2. 8: Effect of Operating Time on Flux (Russel & Kumar, 2017)

In a related context, it was found that the thickness of cake layers is contingent upon the operational duration of the plant (Shahidul & Michael, 2022). Parallelly, Li et al. (2022) undertook similar research demonstrating a gradual increase in energy consumption in UFM with prolonged plant operation. The findings of this study imply that an extended operational period of a UFM without BW and CEB negatively impacts its performance.

2.10 Effect of Process Control Devices on the Performance of UFM

Paulen and Fikar (2016), Bernhard and Uwe (2016) and Huang et al. (2009) discovered the impact of the process control device on the performance of UFM. The reports confirm the efficacy of the process control device within the UFM system, successfully monitoring and controlling TSS, bacteria, colloidal particles, and turbidity in the product water. Additionally, the device plays a key role in optimizing permeate flux and, to some extent, reducing energy consumption. Huang et al. (2009) stated that the process control system in the UFM plant was an effective tool for eliminating bacteria, colloid materials, suspended particles, turbidity, and a portion of total organic carbon from the feed water. Appels et al. (2011) installed a process

control device in the UFM plant to optimize permeate flux and energy consumption rate by controlling the factors that affect the performance.

A few researchers also used process control system in optimizing the permeate flux, energy consumption, and operating cost (Suwaileh et al., 2020; Ahmed et al., 2019). Research findings indicate that real-time monitoring technology serves as an efficient process control tool for tracking colloidal particles and nanoparticle concentrations in feed water. Its application proves instrumental in mitigating cake layer formation on the UFMsurface. Consequently, real-time monitoring emerges as a valuable asset in UFM plant operations, optimizing permeate flux, minimizing energy consumption, and reducing operating costs. The operational mechanism involves an instrument transmitting signals to a controller, which in turn manipulates both a control valve and a pump. Maintaining the set point for the controller is crucial to achieve the minimum operating flow required for the pump. During normal operation, it is imperative for the flow to surpass the minimum flowrate. Failure to meet this criterion prompts the controller to command the control valve to increase its opening, subsequently enhancing pump capacity. Figure 2.9 demonstrates that the higher the head, the lower the flow. At the head, which is below 60ft, there is no flowrate. There will be a flowrate when the head is approximately 61-70 ft with a rough estimate flowrate of 50 gpm (Al-Khalifah & Mcmillan, 2022).

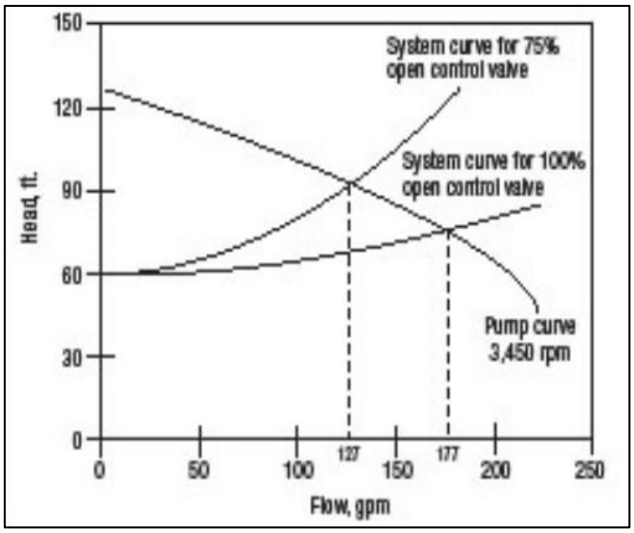


Figure 2. 9: VFD VS Control Valve for Pump Control Valve

2.10.1 Relationship between Pressure Controllers and Feed Flow Controllers

Pressure is a critical parameter essential for continuous monitoring to maintain consistent levels, particularly in membrane filtration processes, ensuring optimal production. In industrial settings such as desalination plants employing Reverse Osmosis (RO) and Nanofiltration (NFM), pressure control, while pivotal, seldom stands alone as the sole control function (Das et al., 2024). In practice, the pressure controller and flow controller often share similarities, functioning as versatile control devices. In the context of UFM (UFM), the feed pressure serves the crucial role of aligning with operational design parameters, ensuring it stays within prescribed limits. Additionally, it plays a key role in mitigating the occurrence of excessive flux at the UFM membrane.

2.10.2 Impact of Process Control on UFM's Productivity

The Proportional, Integral, and Derivative (PID) controller stands as a cornerstone in the process industry. Functioning as a pivotal component within control systems, this mechanism serves to attain desired values for the system. Analogous to the cognitive function of the brain, control systems are integral to managing intricate processes effectively. Figure 2.10 demonstrates the PID process control. The following expounds upon the theoretical aspects of the controller's implementation within the control system (Filo et al., 2023).

i. To improve the steady-state accuracy by decreasing the steady state error. In addition, improves the stability
ii. To remove or minimize offsets produced by the system.
iii. To control the maximum overshoot of the system.
iv. To eliminate the noise signals produced by the system.
v. To increase a better respond of overdamped system overdamped system.

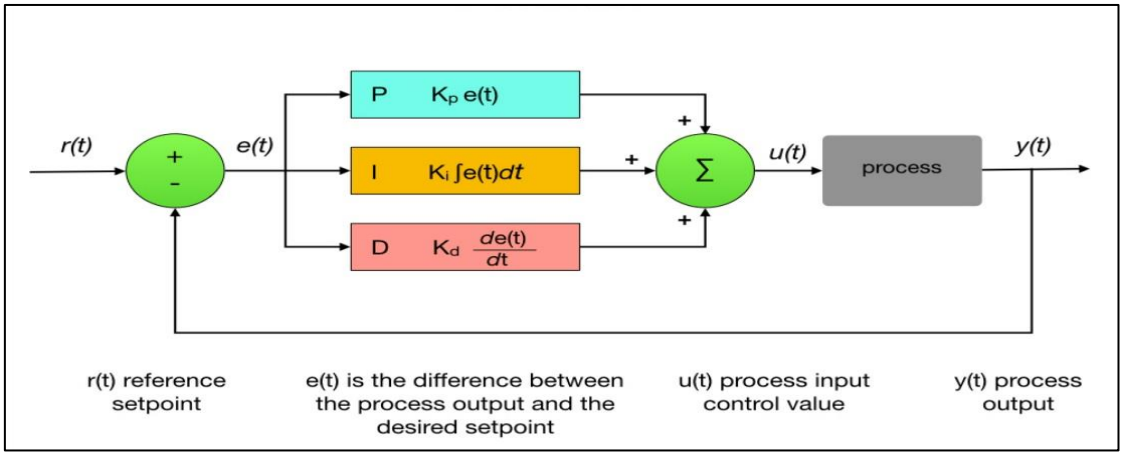


Figure 2. 10: PID Process Control (Filo et al., 2023)

There are three types of basic control which are (i) Proportional controller, (ii) Integral controller, and (iii) Derivative controller.

2.10.3 Proportional Controllers

For a proportional controller, there are three values needed for proportional control.

i. Setpoint (desired value)

ii. Process Variable (Actual value)

iii. Error (Setpoint – Process Variable)

The proportional controller is mathematically defined, with its output, known as the actuating signal, directly correlating with the error signal. Equation 2.15 presents a model of error (Acharya & Das, 2023).

$$y(t) \ \alpha \ e(t)$$ **(Equation 2.15)**

By removing the sign of proportionality, the Equation 2.16 can be expressed as:-

$$y(t) = K_P \, . \, e(t)$$

(Equation 2.16)

where K_P is proportional constant (also known as controller gain). In proportional control, it is crucial to minimize the deviation between input and output, ensuring that any disparities remain within a manageable range. Additionally, it is imperative to avoid abrupt or sudden changes in the deviation. It is recommended that K_P is greater than unity (>1), than it will amplify the error signal. A heightened error signal amplification facilitates more efficient detection. The proportional controller offers the dual benefits of enhancing system stability and minimizing steady-state errors. Furthermore, the sluggish response of an overdamped system can be enhanced for greater speed through the application of this controller.

2.10.4 Application of Process Controllers in Plant Output Optimization

An optimization of the process can be achieved in a such that parameter is one of the factors to the optimum production. Parameters such as temperature, pressure, flow, and conductivity are to be calculated according to the process engineering design. An optimization of the operation or process of the UF plant can be guided as follows (Faisal et al., 2023).

The optimization of ultrafiltration (UF) plant operations significantly benefits from the strategic application of process controllers. These controllers, such as PID (Proportional-Integral-Derivative), play crucial roles in maintaining and adjusting key operational parameters such as pressure, and flow rate to achieve optimal plant performance.

PID controllers are widely used for their simplicity and effectiveness in managing linear systems, making them ideal for controlling temperature and flow rates in UF plants. However, they may fall short in handling complex, nonlinear processes without adequate tuning (Faisal et al., 2023). Fuzzy logic controllers offer a solution for systems with high levels of uncertainty or imprecision, providing better handling of nonlinearities compared to traditional PID controllers, though at the cost of increased complexity in design and implementation (Smith et al., 2021).

In UF plants, maintaining optimal operating parameters with PID controllers or adaptive features helps enhance permeate flux and reduce fouling. Pressure optimization, crucial for maximizing permeate flux while minimizing membrane fouling, is efficiently managed using PID and model predictive controllers (MPC) controllers, with MPC providing superior management of long-term trade-offs between flux and fouling (Faisal et al., 2023). Consistent flow rate control, aligned with membrane supplier specifications, is

typically achieved using PID controllers, with fuzzy logic controllers applied in more complex systems (Smith et al., 2021).

The implementation of process controllers has been shown to enhance plant performance, reduce fouling, and improve energy efficiency. Studies have reported significant increases in permeate flux and reductions in fouling rates and energy usage with the adoption of advanced control systems. For instance, research by Smith et al. (2021) demonstrated a 15% increase in permeate flux with MPC implementation in UF plants, while Johnson et al. (2022) highlighted a 20% reduction in fouling rates using adaptive control systems. Additionally, Lee and Kim (2020) reported a 10% reduction in energy usage with fuzzy logic controllers.

In conclusion, process controllers are indispensable for the optimization of UF plant operations. Their ability to maintain critical parameters within optimal ranges results in enhanced plant performance, reduced fouling, and improved energy efficiency. The choice of controller should be tailored to the plant's specific needs and complexity, with advanced controllers like MPC and adaptive controllers offering significant advantages for complex and dynamic systems (Faisal et al., 2023; Smith et al., 2021; Johnson et al., 2022; Lee & Kim, 2020)

2.11 Water Production Optimization from Membrane by Process Control System

The UFM process presents numerous advantages in water filtration, making it a prevalent choice, particularly in surface water and wastewater treatment. However, optimizing this technology is essential due to its susceptibility to various influencing factors. Li et al. (2023) stipulated that the process of water filtration can be optimized if the following

fields are identified: the understanding of roles of process control system water treatment and the importance of mathematical model on production optimization.

Various mathematical models are being adopted in studies related to the UFM operations to enhance the performance of water filtration. Currently, more attention is given to the development of accurate models in water filtration. Song et al. (2023) reviewed the different types of mathematical models on the optimization of water filtration, which ranges from simple, steady-state models to very complicated models.

Optimizing water filtration draws inspiration from Operations Research. This approach empowers decision-makers to strategically formulate effective solutions. Within the realm of optimization problems, the primary goal is typically to minimize or maximize a function by adjusting variables while adhering to specific constraints. In linear programming, the optimization problem can be solved by the following mathematical models:

Maximizing objective function,

$$Z = C_1X_1 + \cdots + C_nX_n \qquad \textbf{(Equation 2.17)}$$

Subject to constraints,

$$a_1X_1 + \cdots + a_nX_n < b_1 \qquad \textbf{(Equation 2.18)}$$

$$a_mX_1 + \cdots + a_mX_n < b_m \qquad \textbf{(Equation 2.19)}$$

$$X_1 > 0, \cdots, X_n > 0 \qquad \textbf{(Equation 2.20)}$$

The typical input-output production optimization is presented in Figure 2.9.

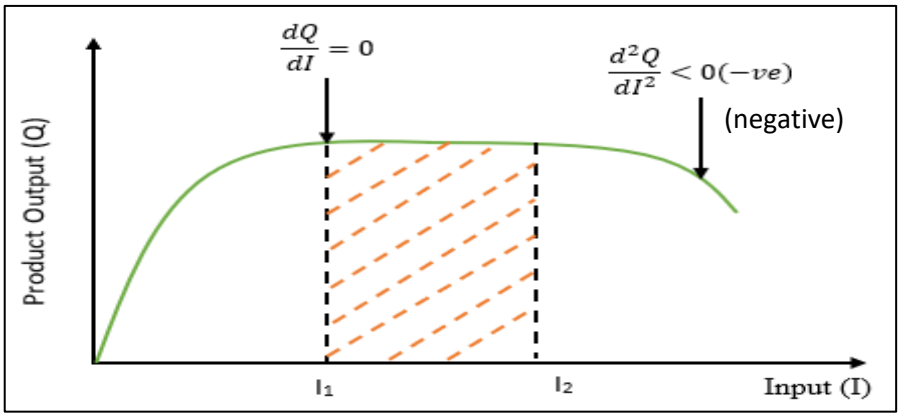


Figure 2. 11: Input-Output Optimization (Burdett, 2016)

Based on Figure 2.11, the maximum output is produced at input I_1 and the point in which $\frac{dQ}{dI} = 0$ is known as the optimum point. Although input I_2 is greater than input I_1 ($I_2 > I_1$), the amount of output is still the same ($Q_{I1} = Q_{I2}$). Therefore, the system should be operated at optimum point of I_1 and Q_{I1}. Beyond the optimum point, the shaded regions under the curve are known as non-value- added inputs. These non-value-added inputs (between I_1 and I_2) may contribute to wastage of energy and productivity. This may affect the production cost and reduce the effectiveness of the output production.

2.12 Central Composite Design for Optimization by Process Control System

The central composite design stands out as the predominant choice in response surface designed experiments. These designs, whether factorial or fractional factorial, incorporate center points and are enhanced by the inclusion of axial points, commonly referred to as star points. The strategic placement of these axial points allows for accurate curvature estimation. This versatile design is instrumental in efficiently estimating both first- and second-order terms. By integrating center and axial points into an existing factorial design, a central composite design can effectively model response variables with curvature. Central composite designs prove especially beneficial in sequential experiments, allowing

the expansion of previous factorial experiments through the incorporation of axial and center points. These designs exhibit the sought-after properties of orthogonal blocks and rotatability, as explained below. Orthogonal blocks in Central Composite Designs are pivotal for conducting experiments with multiple blocks. These designs facilitate the estimation of model terms and block effects independently, ensuring minimal variation in regression coefficients. The concept of orthogonality enhances the precision of parameter estimates. Additionally, the notion of rotatability is crucial in experimental design. Rotatable designs maintain constant prediction variance across all points equidistant from the design center. This feature enhances the reliability of predictions and provides a robust framework for analyzing the effects of independent variables on the experiment's outcome. Design of Experiments (DOE) encompasses a suite of techniques dedicated to scrutinizing the impact of diverse variables on controlled experiments. The process involves identifying independent variables or factors influencing a product or process and evaluating their effects on a dependent variable or response. This report exemplifies the application of Central Composite Designs within a DOE design folio in Weibull+. The objective is to discern optimal factor settings that yield the desired response. By leveraging these statistical tools, we aim to enhance the efficiency and precision of experimental outcomes.

2.12.1 Fundamental of Central Composite Design

Central Composite Design (CCD) stands as a prevalent statistical approach, rooted in the multivariate nonlinear model, extensively applied for optimizing biodegradation process variables. This method not only discerns regression model equations and operating conditions through meticulous experimentation but also proves instrumental in dissecting the intricate interactions among diverse parameters influencing the overall process. The

CCD can be used for fitting a second-order model which requires only a minimum number of experiments for modelling. Basically, the optimization process involves three major steps:

i. Performing the statistically designed experiments,
ii. Estimating the coefficients in a mathematical model, and
iii. Predicting the response and checking the adequacy of the model.

In order to analyze the effect of parameter interactions, the following Equation 2.21 may be applied:

$$Y = \beta_O + \beta_i x_i + \beta_{ij} x_i x_j + \beta_{ii} x_{ii}^2 + \epsilon \qquad \textbf{(Equation 2.21)}$$

where Y is the response variable; β_O is the intercept; β_i, β_{ij} and β_{ii} are coefficients of the linear effect, double interactions; x_i, x_j are the independent variables or factors and ε is the error (Arunkumar et al., 2014).

In RSM method, the least square multiple regression methodology is usually applied to investigate the relationship between the independent and dependent variables. A multiple regression equation can be used to fit the second-order polynomial equation based on the experimental data as in Equation 2.21 (Ghorbannezhad et al., 2016). The regression coefficients that have a statistically significant effect on response should be considered in the equation. Therefore, if the quadratic terms are not statistically significant, those coefficients are removed, and the equation will be linear (Yolmeh & Jafari, 2017).

Statistical experimental designs serve as potent instruments for swiftly identifying key factors within a multivariable system. The Plackett-Burman design stands out as a widely employed method for sequentially screening multiple factors. This approach proves especially valuable in the preliminary stages, focusing solely on estimating the main effects to streamline the screening process. The screening experiments yield crucial factors that can

be fine-tuned through response surface methodology (RSM), enabling the exploration of interaction effects among variables. For instance, the optimization of media components for laccase production in various fungal strains has been successfully accomplished using RSM. Therefore, RSM, a statistical experimental technique employed within a well-designed experiment, proves instrumental in solving multi-variable equations.

2.12.2 Detail Steps of Central Composite Design

Central Composite Design (CCD) is a sophisticated response surface design featuring 3-level factors augmented by axial or star points, denoted as (α). These axial points expand the design to 5 levels, enhancing experimental flexibility. This extension empowers the designer to assess the impact of factors beyond or below the initially chosen levels. CCD accommodates a minimum of two numerical or continuous factors, making it a versatile tool for intricate experimental designs. The number of experimental runs obtained at each number of factors is given by the formula in Equation 2.22.

$$N = 2^n + (2 \times n) + nc \qquad \textbf{(Equation 2.22)}$$

where, N is the number of experimental runs = $\emptyset$; n is the number of factors or number of repetitive of data collection; nc is the number of centers points of design.

2.12.3 Response Surface Methodology on Water Production Optimization by UFM

Response Surface methodology (RSM) is a collection of mathematical and statistical techniques useful for developing, optimizing, and improving products and industrial processes. It has become the most popular multivariate statistical technique used in the optimization process industries (Baş & Boyacı, 2007). Response Surface Methodology

(RSM) proves particularly valuable in scenarios where multiple factors impact production, yield, or the percentage removal in a given process. Originating from the design of experiments (DOE), RSM serves to identify the crucial factors influencing an experiment. Its primary objective is to minimize the number of experimental runs while optimizing output based on the generated data. This data, in turn, allows for the development of practical models that establish correlations between the response and the experimental factors. Consequently, the model facilitates the exploration of a more effective process response, which is subsequently validated through additional experiments. The model iterates till an optimal process is identified or the limit of experimental resources is reached (Danmaliki et al., 2017). Response Surface Methodology (RSM) comprises a set of statistical and mathematical techniques based on fitting a polynomial model to data. This model aims to accurately represent the behavior of a dataset, with the primary objective of enabling statistical predictions. RSM proves valuable in optimizing, designing, developing, and improving processes wherein one or more responses are influenced by multiple variables (Ghorbannezhad et al., 2016; Kaushik et al., 2006). The objectives of response surface methodology encompass both the determination of optimal variable settings, where the mean response is optimized, and the estimation of the response surface in the vicinity of this optimal configuration.

2.13 Use of Design of Experiment on Water Production Optimization

Upon conducting a thorough literature review, it becomes evident that the Design of Experiments (DoE) methodology is particularly well-suited for both input and output design research. The crux lies in comprehending the variables and experimental ranges, as they play a pivotal role in ensuring that the input variables result in the desired outcomes. This

understanding is essential for establishing models that correlate inputs with the outputs of the process.

The mathematical relationships between Critical Process Parameters (CPPs) and Material Attributes (CMAs) with Critical Quality Attributes (CQAs) delineate the design space. As a consequence, a deep understanding of the process is achieved, systematically leading to a final output that aligns with the Maximum Target Desired Profile (MTDP). This robust approach not only assures process understanding but also rationalizes the journey from inputs to outputs, ensuring the end result meets the desired quality Fractional factorial 5-level designs could be used for our analysis, as follows:

i. Selection of process variables and response: this choice is justified based on the DoE objective and should ensure that the entire design is executable and appropriate for satisfying its scope. This means that factor types are either numeric or categorical and their levels, i.e., their values within the design, are selected accordingly.

ii. Take the value of 5 levels (-α, -1, 0, 1, α) factor: this result can justify the range between each level.

iii. Selection of an experimental design (RSM, CCD): based on DoE objectives, screening, characterization or optimization of process and formulation, several types of designs can be chosen, e.g., factorial or mixture. Decisions on randomization, blocking, and replications should be also addressed.

iv. Checking the data with the experimental design: DoE are exceptionally effective in identifying outliers arising from potential poorly executed trials.

v. Analyzing the results: ANOVA and graphical tools are very helpful in identifying main effects of the significant factors and their interactions. The results are evaluated not

only on a statistical basis but also based on the established theories, leading practically to process knowledge.

vi. Use and interpretation of the results: at this step, the evaluation of the DoE outcome can support scientifically sound decision making on following actions, such as executing confirmatory runs, augmenting designs, or further proceeding with scale-up and technology transfer activities. It is evident that the success of these seven steps heavily depends on the establishment of an appropriate environment that can support the seamless execution of the DoE.

vii. Check the correlation and intercept in between input variables.

viii. Report with graph collection based on run, predicted and actual values.

ix. Generate 3D graphs with optimum values for specific variables for highest output.

x. Visualize the central composite design (CCD) for optimum level of outputs.

2.14 Statistical Model for Hypothesis Test

2.14.1 The P-value

In this section, we will introduce the concept of the P-value, which provides only surface-level information for this research. The P-value represents the odds of obtaining an effect that is equal to or substantially greater than the one observed under the null hypothesis condition. This effect could pertain to any measure of relationship between two variables or a difference in measurement between two groups. Biau et al. (2010) offer a comprehensive explanation of the P-value and the theory of hypothesis testing in their article, targeting new researchers (Clinical Orthopaedics and Related Research, 468, 885-892). The concept of the P-value was introduced by mathematician Karl Pearson in 1900 through his chi-square test.

However, it was Sir Ronald A. Fisher, often regarded as the father of modern statistics, who in 1925 provided the first method for calculating the P-value across a wide range of circumstances (Fisher, 1925).

2.14.2 Probability Event and Statistical Significance

A more refined objective of statistical analysis aims to offer an assessment of certitude or ambiguity concerning the magnitude of an effect. Hung et al. (1997) examined the behavior of the P-value in cases where the alternative hypothesis holds true. In their research published in Biometrics, they investigated the dynamics of P-value under such conditions (Vol. 53, No. 1, pp. 11-22) that it is customary to quantify such certitude through the lens of "probabilities" related to hypotheses. Within conventional statistical methodologies, the term 'probability' is not applied to hypotheses; rather, it pertains to hypothetical frequencies of data patterns within an assumed statistical model. These methodologies are known as frequentist methods, and the envisioned frequencies are specifically termed 'frequency probabilities.' Despite rigorous training, a common tendency persists among many statistically educated professionals to misinterpret these frequency probabilities as probabilities related to hypotheses. Complicating matters further, statisticians reserve the term 'likelihood of a parameter value' to denote the probability of observing the given data under the assumed parameter value. It does not indicate the probability of the parameter assuming the specified value. The author Greenland et al., (2016) stated that these issues are particularly pronounced in applications of a hypothetical frequency known as the P-value, also termed the "observed significance level" for test hypotheses. Statistical "significance tests" founded on this concept have long been a core

facet of statistical analyses. Raftery et al. (1995). The discussion on hypothesis testing and modeling in the book "Markov Chain Monte Carlo in Practice" delves into various aspects, particularly emphasizing the application of Markov chain Monte Carlo methods (pp. 165-187). The authors assert that conventional definitions of P-value and statistical significance predominantly center around null hypotheses, treating all other assumptions used for P-value computation as established certainties.

Recognizing the frequently dubious or unjustified nature of these assumptions, the authors advocate for a more comprehensive interpretation of the P-value. They suggest conceptualizing it as a statistical encapsulation of the alignment between observed data and the hypothetical scenario that underpins the entire statistical model. This broader perspective entails considering all assumptions incorporated into the computation of the P-value. In the work by Anderson et al. (2000), the focus is on the shortcomings and common issues associated with null hypothesis testing. This study thoroughly examines the challenges and widespread issues stemming from the traditional approach to hypothesis testing. In response, the authors propose an alternative perspective to tackle these concerns. The study's findings emphasize the need for a critical reassessment of the limitations associated with null hypothesis testing, advocating for a transition to a more comprehensive and effective methodology. Specifically, the divergence between the data and model prediction is measured using a test statistic (such as a t-statistic or Chi-squared statistic). The P-value in this context signifies the likelihood that the selected test statistic would equal or exceed its observed value under the assumption that every model assumption, including the test hypothesis, is accurate. This clarification highlights a crucial aspect often overlooked in conventional definitions: logically, the P-value scrutinizes all assumptions related to data generation (the complete model), not solely the targeted hypothesis (such as a null

hypothesis). Furthermore, these assumptions encompass more than just conventional modeling or probability factors; they extend to suppositions about the conduct of analysis, including whether intermediate outcomes influenced the selection of presented analyses. In his comprehensive guide on hypothesis testing, Frost (2021) provides an insightful explanation of hypothesis tests offers a clear and accessible breakdown of these testing approaches. Frost's article explores the distinctions between one-tailed and two-tailed tests, elucidating how each method is used to evaluate different types of research questions. By delving into the nuances of hypothesis testing, Frost's work provides valuable insights for researchers seeking a better understanding and application of these techniques in their statistical analyses. A lower P-value suggests that the data would be more unusual if every assumption were correct. However, a small P-value does not pinpoint which assumption is incorrect. For example, the P-value may be small due to a false targeted hypothesis or as a result of protocol violations or selection bias. Conversely, a high P-value simply indicates that the data are not anomalous within the model, without endorsing the model or any of its components, such as the targeted hypothesis. A high P-value might result from protocol violations or selection bias. Kimmel (1957) state that the broad P-value definition elucidates why statistical tests convey less information than commonly assumed. A P-value does not affirm hypothesis veracity; it warrants no conclusion tied to the hypothesis unless every computation assumption is certain - a shortfall in numerous studies. Nonetheless, as presented in Figure 2.12**,** the P-value can be perceived as a continuous gauge of data-model compatibility, ranging from 0 (complete mismatch) to 1 (complete alignment). This representation measures model-data fit. In the work of Kim and Bang (2016), the authors address three prevalent misinterpretations associated with P-value and regrettably, the P-value is often relegated to a dichotomy where results are "statistically significant" if P is ≤

0.05 and "nonsignificant" otherwise. Terms like "significance level" and "alpha level" (α) denote the cutoff, but "significance level" confusion arises between the cutoff and the P-value itself. The distinction is profound: α is preset and part of study design, untouched by data. In contrast, the P-value emerges from data and remains unknown until computed.

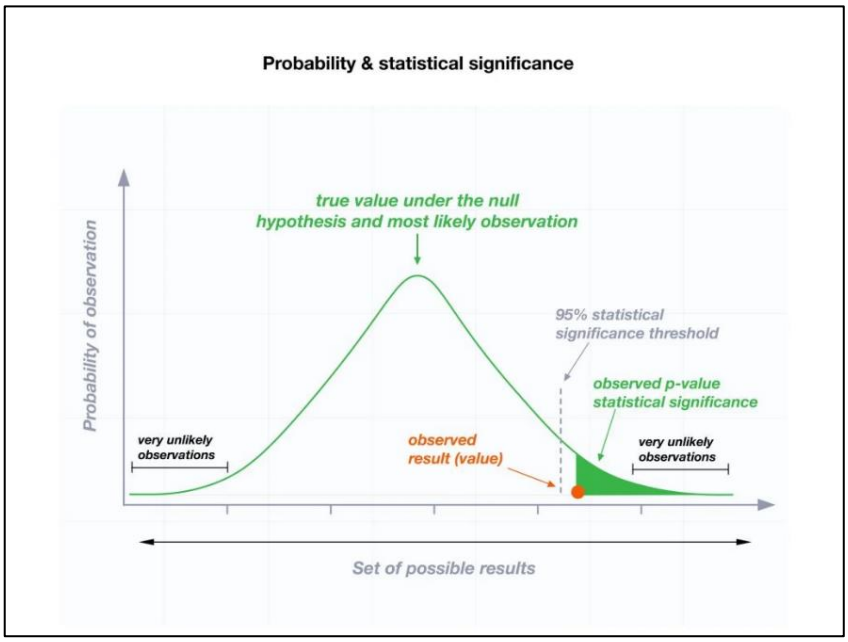


Figure 2. 12: Probability & Statistical Significance Test (Kim & Bang, 2016)

2.14.3 Test to Estimate P-value

One can manipulate the test hypothesis while keeping other assumptions constant to explore variations in the P-value across different test hypotheses. These hypotheses often specify distinct magnitudes for the targeted effect. In a study by Azam and Khan (2016), an empirical investigation was conducted to assess the validity of the Environmental Kuznets Curve hypothesis across various income categories, including low, lower-middle, upper-middle, and high income. The study examined the relationship between Pressure Controllers and Feed Flow Controllers in different countries, providing examples. The value assessed in

these hypotheses might focus on determining whether the average disparity between two treatment groups is zero (null hypothesis), 20, -10, or any other relevant magnitude. The effect size that yields a P-value of 1 aligns most harmoniously with the data's predictions under accurate assumptions in the test (statistical model). This provides a point estimate of the effect based on these assumptions. Effect sizes resulting in $P > 0.05$ usually define a range (e.g., 11.0 to 19.5) that aligns closely with expected observations if the model were accurate. This range represents a 95% confidence interval, concisely summarizing the outcomes of hypothesis tests across various effect sizes. Confidence intervals serve as illustrative examples of interval estimates. In 1937, Neyman introduced an approach for constructing confidence intervals. The underlying principle of this method lies in its inherent characteristic: if the approach is valid, 95% confidence intervals will, on average, encompass the true effect size 95% of the time. This reliability is referred to as the coverage probability, which is a property of a sequence of confidence intervals computed from valid models, rather than any individual interval. The discourse surrounding the significance of "significance tests" and their role in statistical inference has seen contributions from various scholars. For example, Atkins and Jarrett (1979) explored the implications of "significance tests" in their effort to demystify social statistics. Cox (1977) engaged in a comprehensive discussion regarding the role of significance tests within the context of statistical analysis. Additionally, Freedman, Pisani, and Purves (2007) delved into the subject of statistics, shedding light on its intricacies and methods. The comprehensive insights provided by these authors contribute to a broader understanding of statistical methods and their applications (Altman et al., 2000; Atkins & Jarrett, 1979; Cox, 1977; Freedman et al., 2007).

While many academic journals now insist on the inclusion of confidence intervals, most scholarly discussions predominantly emphasize P-value for null hypotheses. This

focused attention on null hypotheses not only fosters misconceptions about tests and hampers appreciation of estimation but also obscures the interplay between P-value and confidence intervals, as well as their shared limitations.

2.14.4 General Concept of Statistical Hypothesis

Lehmann et al. (1986) extensively explored the domain of testing statistical hypotheses, providing valuable insights into this area. In a similar vein, Greenland et al. (2016) offered comprehensive guidance on interpreting statistical tests, P-value, confidence intervals, and power, which is highly relevant in the field of epidemiology. These works significantly contribute to enhancing our understanding of statistical methodologies and their appropriate applications. Statistical hypotheses, as elucidated by these researchers, refer to statements concerning a population's parameter, such as the average or variability of a normal population. These hypotheses are rooted in the principle of proving by disproving. Specifically, hypotheses can be examined to determine whether an intervention or experiment has impacted the population's mean. This process involves formulating a null hypothesis based on the absence of any difference.

2.14.5 Hypothesis Testing

This section delves into hypothesis testing to enhance our understanding of how the P-value significantly influences both the independent and dependent variables in research. The impact of the P-value can be observed in various measures of the relationship between two variables or differences in measurements between two groups. In the realm of statistics, a hypothesis is an idea that requires testing to determine its validity. Hypothesis testing

serves as a means to ascertain the truth or falsity of this idea. The Roles of Null and Alternative Hypotheses Hypothesis testing involves two key concepts: the null hypothesis (H_0) and the alternative hypothesis (H_1) by Kock (2016). The null hypothesis posits that entities are distinct and alike, implying an absence of any significant difference. In contrast, the alternative hypothesis proposes a correlation between these entities. Disagreement with the null hypothesis arises when considering the alternative hypothesis. For instance, the null hypothesis may claim that serotonin levels do not influence stress coping, while the alternative hypothesis contends that they do. According to Raftery (1995), hypothesis tests do not necessarily have to explicitly specify the nature of this relationship. Constructing a hypothesis test involves the initiation of a process that begins with formulating both the null hypothesis (H_0) and the alternative hypothesis (H_1). The null hypothesis represents the concept under investigation, while the alternative hypothesis proposes the concept to be proven, contingent on substantial evidence contradicting the null hypothesis.

2.14.6 Null Hypothesis

The null hypothesis, denoted as H_0, posits that there is no change in the variable under investigation. This hypothesis, H_0, is always tested in research. The P-value is then examined and can lead to either the rejection or non-rejection of H_0. For instance, Raftery (1995) provides an example of H_0 in the context of airway suctioning: 'using a closed suctioning system won't lower oxygen drop during airway suctioning.'

2.14.7 Alternative Hypothesis

The alternative hypothesis, denoted as H_1, represents the opposing idea to the null hypothesis (H_0). In the context of hypothesis testing, if the null hypothesis is rejected, the analysis favors H_1. This implies a belief in a significant change in the studied phenomenon after conducting an experiment. The alternative hypothesis is often the central focus of a research paper, as it elucidates the purpose behind the study. In the case presented, H_1 posits that 'using a closed suctioning system will lower oxygen drop during airway suctioning,' as proposed by Raftery (1995).

2.14.8 Assessing Significance of Hypothesis Testing

To assess the strength of evidence against the null hypothesis, researchers establish a significance level (α), which serves as a threshold for the required evidence. A commonly chosen significance level is 5%. Subsequently, data is collected, calculations are performed, and a P-value is derived. The P-value indicates the likelihood of our findings under the assumption that the null hypothesis is correct. Once the P-value is obtained, it is compared to the significance level. If $p < \alpha$, the null hypothesis is rejected, providing support for the alternative hypothesis. Lower P-value indicates stronger evidence against the null hypothesis. Conversely, if $p \geq \alpha$, the null hypothesis cannot be dismissed. Figure 2.13 illustrates how hypothesis significance has been plotted.

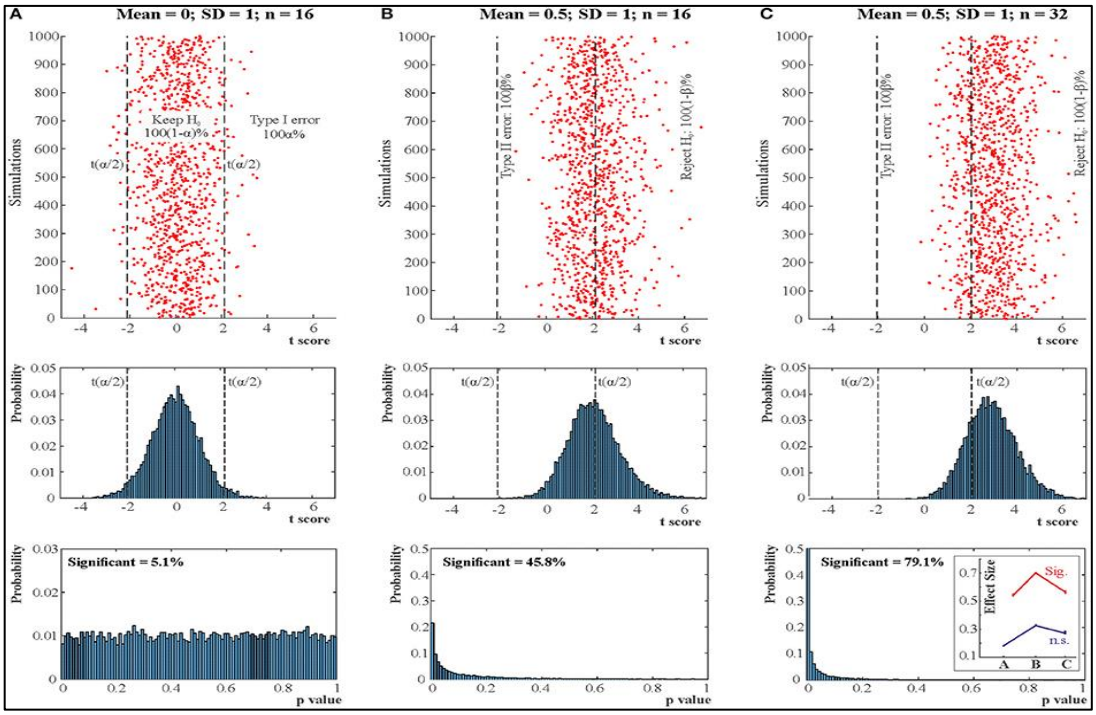


Figure 2. 13: Hypothesis Significance Test by Szucs and Ioannidis (2017)

Alternatively, results can be compared to critical values based on the chosen significance level. For test results:

i. If the results are positive and exceed the critical value, the null hypothesis can be rejected, and the alternative embraced.

ii. If the results are positive but equal to or less than the critical value, the null hypothesis must be accepted.

iii. If the results are negative and fall below the critical value, the null hypothesis can be rejected, and the alternative adopted.

iv. If the results are negative but equal to or greater than the critical value, the null hypothesis must be accepted.

2.14.9 Common Misinterpretations of Single P-value

Taroni et al. (2016) conducted a critical examination of the utilization of statistical hypothesis testing in scientific applications. They emphasized the imperative need to reevaluate the reliance on P-value, as misconceptions about P-value and related concepts have resulted in significant distortions within scientific literature. In order to address this issue, the researchers thoroughly examined prevalent misinterpretations of P-value based on referenced articles. Building upon this perspective, Mark et al. (2016) have made significant contributions to the comprehension of P-value and hypothesis tests within research contexts. Their work enhances the understanding of the role of these statistical measures in investigative processes. In line with this, the present study aims to contribute to the field by presenting a comprehensive list of these misconceptions. The intention is to encourage a critical evaluation of research findings, fostering a more accurate interpretation of statistical results within the scientific community. Newman (2008) has provided a thorough analysis of hypothesis testing, delving into its nuances and implications that the bolded statements in our list have contributed to statistical confusion in scientific discourse. The hypothesis emphasizes "No!" to highlight fallacies that are not only incorrect but also lack practical validity.

1. P-value Misinterpretation: Hypothesis Probability

   Mistake: Thinking that the P-value tells us the probability that the test hypothesis is true.

   Correction: The P-value shows how well the data aligns with the predicted pattern of the test hypothesis, not its probability.

2. P-value Misinterpretation: Chance Alone Produced Association

Mistake: Believing that a P-value > 0.05 means there's a probability that chance alone caused the observed link.

Correction: The P-value assumes that chance operated alone—it is not a probability and does not reflect hypothesis correctness.

3. P-value Misinterpretation: Significance Implies Hypothesis Rejection

   Mistake: Assuming that a significant result ($P \leq 0.05$) means the test hypothesis is false.

   Correction: A small P-value just flags data as unusual, not necessarily due to the test hypothesis.

4. P-value Misinterpretation: non significance implies Hypothesis Acceptance

   Mistake: Believing that a nonsignificant result ($P > 0.05$) supports the test hypothesis.

   Correction: A large P-value indicates data are not unusual, but many other hypotheses may still fit.

5. P-value Misinterpretation: Large P-value Supports Hypothesis

   Mistake: Thinking that a large P-value is evidence for the test hypothesis.

   Correction: A P-value < 1 means the test hypothesis is not the most data-compatible—other hypotheses might be more suitable.

6. P-value Misinterpretation: P-value Indicates Absence of Effect

   Mistake: Assuming that $P > 0.05$ means there is no effect.

   Correction: $P > 0.05$ means null is one of many hypotheses with $P > 0.05$; look at the point estimate for effect size.

7. P-value Misinterpretation: Significance Indicates Important Relation

   Mistake: Believing that statistical significance means a significant relation is found.

Correction: Small P-value only suggests unusual data, not necessarily significant for practical purposes.

8. P-value Misinterpretation: No significance Implies Small Effect

   Mistake: Assuming that a large P-value means a small effect.

   Correction: Large P-value doesn't mean effect size is small; check confidence interval.

9. P-value Misinterpretation: P-value Equals Data Probability

   Mistake: Thinking that P-value is the chance of data under the test hypothesis.

   Correction: P-value refers to data frequency, assuming all computation assumptions are correct.

10. P-value Misinterpretation: Error Chance for $P \leq 0.05$ is 5%

    Mistake: Believing that rejecting the null with $P \leq 0.05$ means a 5% error chance.

    Correction: This misjudges error probabilities, linking to the fallacy number 1.

11. P-value Misinterpretation: $P = 0.05$ Equals $P \leq 0.05$

    Mistake: Assuming $P = 0.05$ and $P \leq 0.05$ have the same meaning.

    Correction: $P = 0.05$ and $P \leq 0.05$ have distinct implications for results.

12. P-value Misinterpretation: P-value as Inequalities

    Mistake: Reporting P-value as inequalities (e.g., $P < 0.02$ or $P > 0.05$) is good practice.

    Correction: Inequalities obscure interpretation; use precision when $P < 0.001$ but avoid it when $P > 0.001$.

13. P-value Misinterpretation: Significance is Phenomenon Property

    Mistake: Thinking that statistical significance is about the phenomenon.

    Correction: "Statistical significance" is about the result, not the phenomenon's existence.

14. P-value Misinterpretation: Always Use Two-Sided P-value.

    Mistake: Believing that two-sided P-value are always necessary.

Correction: One-sided P-value are for specific cases; specify their use when appropriate.

2.15 Gap Analysis of Literature Review

This section aims to provide justification for the current research by delving into the literature relevant to Objectives 1, 2, and 3, as outlined in Chapter 1. An exhaustive literature review has been undertaken to examine the performance of the UFMprocess, specifically focusing on process control devices in relation to permeate flux and energy consumption rate. A thorough analysis of approximately 20 published papers has been conducted to extract the latest findings aimed at enhancing efficiency and addressing process gaps. This review highlights the disparity between previous and current research studies, shedding light on the identified research scope and establishing the novelty of the current study.

2.15.1 Gap Analysis of Literature Review Relating to Objective One

The research findings, as presented in the literature review by authors Rosdianah Ramli and Nurmin Bolong, focus on the effects of transmembrane pressure and feed water temperature on Ultrafiltration Hollow Fiber Membrane in a Mobile Water Treatment System (Ramli & Bolong, 2016). This research paper focuses on the impact of transmembrane pressure on flux in the ultrafiltration (UF) process. It underscores that as transmembrane pressure increases, so does the flux. The paper identifies an operating pressure range between 0.25 and 3.0 bar; however, it notes a decline in flux when the pressure reaches its maximum. Surprisingly, the research paper does not address the effects on process control devices, such as the level sensor and VFD, in relation to permeate flux. Consequently, this study aims to

bridge this gap, and a comprehensive research methodology has been developed to address these aspects.

The second research finding from the literature review focuses on the work of Pervez et al. (2022), who conducted a review on factors influencing pressure-driven membrane-assisted volatile fatty acids recovery and purification. In their study, the authors emphasized that filtration techniques, specifically nanofiltration and reverse osmosis, demonstrated varying percentage recoveries. Notably, the research paper did not address the impact of process control devices, such as level sensors and VFD, on permeate flux. To address this gap in the literature, our research aims to investigate and elucidate the influence of process control devices on permeate flux. This critical aspect, not covered in the previous study, is the focal point of our research. The detailed research methodology outlining our approach and methodologies can be found in Chapter 3, where we systematically develop strategies to bridge this knowledge gap.

The third research finding in the literature review, authored by Ekansh Sharma, focuses on the design and optimization of an UFM setup for wastewater treatment and reuse (Sharma, 2020). This research paper provides an exploration of the literature on diverse configurations within the membrane filtration process. It delves into the influence of various parameters on achieving optimal effluent quality results and enhancing the performance of the ultra-filtration membrane process. However, the existing literature lacks information regarding the impact of process control devices, such as the level sensor and VFD, on permeate flux. Addressing this gap is the primary focus of our research, and as a response, a detailed research methodology has been developed to investigate and bridge this knowledge void.

As a summary of the literature review pertaining to objective 1, this research aims to identify gaps and address them by examining the impact of process control devices, such as level sensors and VFDs, on permeate flux.

2.15.2 Gap Analysis of Literature Review Relating to Objective Two

In their 2020 study, Liu et al. (2020) explored the influencing mechanism of command-and-control instruments (CAC) on the adoption of energy consumption monitoring technology (ECMT) in public buildings. The research paper places a strong emphasis on energy conservation achieved through the integration of command-and-control instruments for energy consumption and monitoring technology. According to the studies conducted by Chen et al. (2017) and Luo et al. (2020), this implementation have proven and demonstrated that the energy save was from 5-15% power consumption of the building sector compared to conventional sector. The application and concept discussed here are increasingly prevalent in energy-saving applications. These reports are closely aligned with current research on power usage for energy conservation. The conceptual design application has the potential to enhance energy-saving measures and can be employed in the ongoing research study on this subject. However, a notable gap has been identified in the application process, particularly concerning the omission of crucial devices like the level sensor and VFD in assessing energy consumption rates. Consequently, this research aims to address and rectify these gaps, ultimately striving to achieve its objectives and contribute to a more comprehensive understanding of energy-saving applications. The research paper, authored Sayed et al. (2020) focuses on the monitoring and rationalization of energy consumption in home electric appliances. This research paper introduces a novel device designed for

monitoring energy consumption in homes, employing a wireless Arduino controller. Energy monitoring systems, as highlighted by Miquel et al. (2013) offer enhanced and convenient real-time information regarding power consumption. Furthermore, the system incorporates a foundational model to rationalize electricity consumption, as discussed by Josue et al. (2011). The application not only facilitates user-friendly monitoring but also allows installation on mobile devices for seamless access. According to these authors, one of the most effective way to control and rationalize the power consumption by using smart devices (Ryan, 1988). Having acknowledged this, it is essential to optimize energy consumption effectively. The proposed conceptual design holds significant potential for application in ongoing research, enabling the monitoring and rationalization of process control for enhanced power efficiency and reduced energy consumption. Nevertheless, a notable gap exists in the current understanding, as application process control devices, such as the level sensor and VFD, have not been considered in relation to the energy consumption rate. Therefore, the primary objective of this research paper is to address this identified gap and present the developed methodology for comprehensive coverage. According to Akthar et al. (2020), in their research paper, data is important in order to implement the energy saving strategies. The objective of the research paper was to illustrate the influence of energy monitoring and management systems on enhancing energy efficiency in the industrial sectors of developing countries. According to the findings, the implementation of systems like SCADA, coupled with the integration of Modbus and industrial ethernet, can result in an approximate 8% improvement in energy efficiency. The SCADA system, widely employed in various industries, can be pre-designed for effective real-time monitoring and control of energy consumption (Işik et al., 2018). SCADA, once a common programmable logic controller (PLC), is now less prevalent due to its integration being a part of PLC usage for

control and monitoring (Priyanka et al., 2019). Despite its decline, SCADA has found new relevance in the realm of cloud databases. Priyanka et al. (2019) introduced a SCADA-based energy management system in a cloud database, opening avenues for research in areas such as energy efficiency management, control, monitoring, and cost efficiency. However, a notable gap has been identified in the existing literature, specifically in the omission of application processes involving control devices like level sensors and VFDs (VFD) in the SCADA system. To address this gap, our research paper aims to narrow down the missing elements, and to achieve this, a comprehensive research methodology has been developed.

2.15.3 Gap Analysis of Literature Review Relating to Objective Three

The research findings discussed in the literature review written by the authors Robert W. Field and Jun Jie Wu on permeate flux in ultrafiltration processes – understandings and misunderstandings (Field & Wu, 2022), delve into various aspects of ultrafiltration. The paper elucidates concepts such as concentration polarization, the osmotic model, fouling, modes of fouling, and design. Within the context of item 3, which addresses the topic of 'Modeling the Flux Decline,' the research paper underscores the importance of determining an appropriate classification for flux decline models. This research paper was supported by the author of researcher (Quezada et al., 2021; Kirschner et al., 2019; Wu, 2021). Nevertheless, the current literature lacks information regarding the process optimization of UFMconcerning permeate flux, feed pressure, and energy consumption rate, utilizing Design of Expert (DOE) software, version 13. This research aims to bridge this gap by developing a targeted approach. A comprehensive research methodology has been formulated for this purpose.

The literature review conducted by Ren et al. (2019) presents research findings in their paper titled Pilot Study on the Effects of Operating Parameters on Membrane Fouling during Ultrafiltration of Alkali/Surfactant/Polymer Flooding Wastewater: Optimization and Modeling. The primary focus of this study is to investigate the impact of transmembrane pressure on output flux. The results reveal a direct correlation: as transmembrane pressure increases, the flux also experiences a corresponding rise. However, a higher application of transmembrane pressure leads to more severe membrane fouling, resulting in a significant decline in the operational process efficiency. In Figure 2.14 below, the flux demonstrates a continuous increase, indicating the instantaneous variation of transmembrane pressure. Notably, this research paper does not elaborate on the process optimization of UFMconcerning permeate flux, feed pressure, and energy consumption rate using the Design of Expert (DOE) software, version 13. To address this gap, this research is specifically targeted at reducing these disparities, and a comprehensive research methodology has been developed. This process is where the permeate flux decreased due to densification of membrane (*Pilot Scale Investigation of Microfiltration Performance and Reuse Potential for Water and Wastewater Suwanna Kitpati*, 1998).

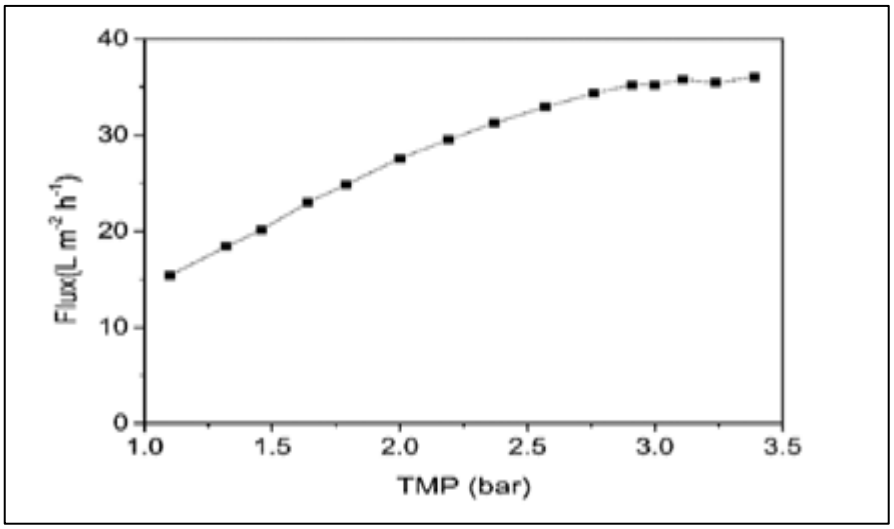


Figure 2. 14: Effect of Transmembrane Pressure on Instantaneous Output Flux (Ren et al., 2019)

The research gap identified in this paper pertains to the omission of applying the optimum transmembrane pressure in the research process. The findings reveal that the transmembrane pressure falls within the range of 2.8-3.2 bar, while the manufacturer's recommendation is 1.5 bar. Notably, there is a lack of information regarding the process optimization of UFM concerning permeate flux, feed pressure, and energy consumption rate. The Design of Expert (DOE) software, version 13, has been chosen for this optimization process. The primary aim of this research is to address and minimize this gap. To achieve this, a research methodology has been developed. Table 2.2 illustrates the performance of UFM in water filtration, specifically highlighting its effectiveness in portable water production. The existing gap in published research regarding the membrane's application in this context is also identified.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview of Research Methodology

This chapter outlines the experimental setup employed to conduct the research in this study. The necessary equipment was organized and installed in accordance with the research goals. Chapter 3 provides a detailed account of the experimental setup, the procedures for conducting experiments, and the methods employed for data analysis. The research focus is on optimize the performance of the UFM in permeate flux yield [$m^3(sqm)^{-1}$] in respect of the energy consumption rate ([$kW(m^3)^{-1}$]) and feed pressure. The outline of Chapter 3 is presented in the following sections. Section 3.2 describes the research design of the experiment, while the details pertaining to the objectives are discussed in Sections 3.2.1, 3.2.2, and 3.2.3. The research variables are explicitly stated in Section 3.3, and the data analysis method is outlined in Section 3.4. The theoretical framework of this study is elaborated upon in Section 3.5. Finally, the chapter concludes with a summary in Section 3.6.

3.2 Research Design for Achieving Objective

The primary objective of this study is to assess the impacts of process control devices. To attain this goal, the study is structured around three specific objectives, as illustrated in Figure 3.1.

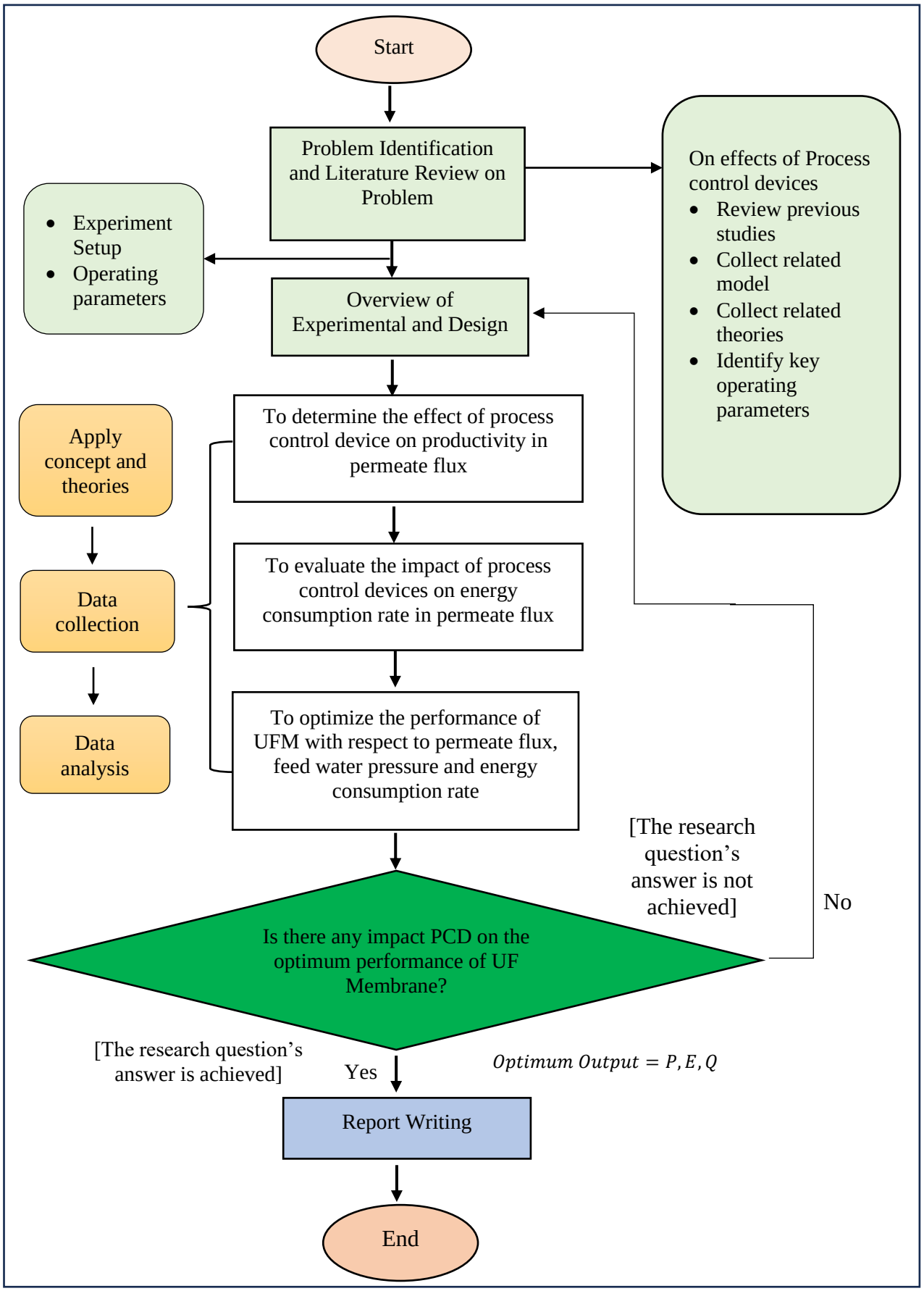


Figure 3. 1: Research Methodology of Study

The research methodology has been meticulously crafted to align with the specific objectives of this study. It is structured into several sections and subsections to ensure a systematic and comprehensive approach. The overarching theme of the research design is to achieve the primary objective of this study, which is an impact of process control devices on the performance of UFM regarding key parameters such as energy consumption rate ([kW(m^3)$^{-1}$]), permeate flux yield [m^3(sqm)$^{-1}$], and feed pressure. The principal equipment employed for this experiment includes the UFM, feed water pump, and process control devices (the latter comprising a VFD and a water level sensor in the tank).

Research Methodology Step 1.0 pertains to objective 1.0, which seeks to assess the evaluate the effect of process control devices on the productivity of permeate flux rate (expressed in [m^3(sqm)$^{-1}$]). In pursuit of this objective, the research protocol involves the operation of an UFMplant in two distinct phases. In the initial phase, the experimental setup will be executed without the incorporation of process control devices in conjunction with the UFM system to generate permeate flux. Subsequently, in the second phase, the experiment will be executed with the incorporation of process control devices, thereby enabling the generation of permeate flux solely in the performance of UFM.

Research Methodology Step 2.0 is dedicated to addressing Objective 2.0, which aims to evaluate the impact of process control devices on the energy consumption rate (expressed in [m^3(sqm)$^{-1}$]). In pursuit of this objective, the research protocol involves the operation of an UFMplant in two distinct phases. In the initial phase, the experimental setup will be executed without incorporating the utilization of process control devices in conjunction with the UFM system to generate energy consumption rate. Subsequently, in the second phase, the experiment will be executed with the incorporation of process control devices, thereby enabling the generation of energy consumption rate solely in the performance of UFM.

Research methodology step 3.0 corresponds to objective 3.0 which aims to optimize the performance of UFM in terms of feed water pressure(bar), energy consumption rate [kW$(m^3)^{-1}$] and permeate flux [$m^3(sqm)^{-1}$].

3.3 Experimental Set Up and Operation

The schematic diagram of equipment used for conducting experiment present in Figure 3.2.

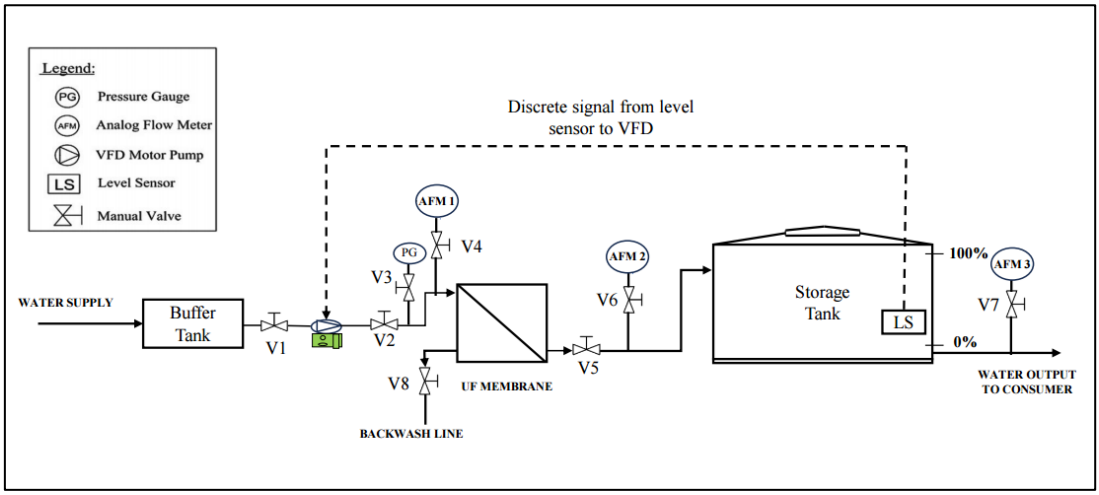


Figure 3.2: Schematic diagram to Achieve the Objectives

The key equipment's are buffer water storage tank, feed water pump with VFD, UFM, product water storage tank, level sensor, and valves.

Figure 3.3 (a): Experimental Set Up

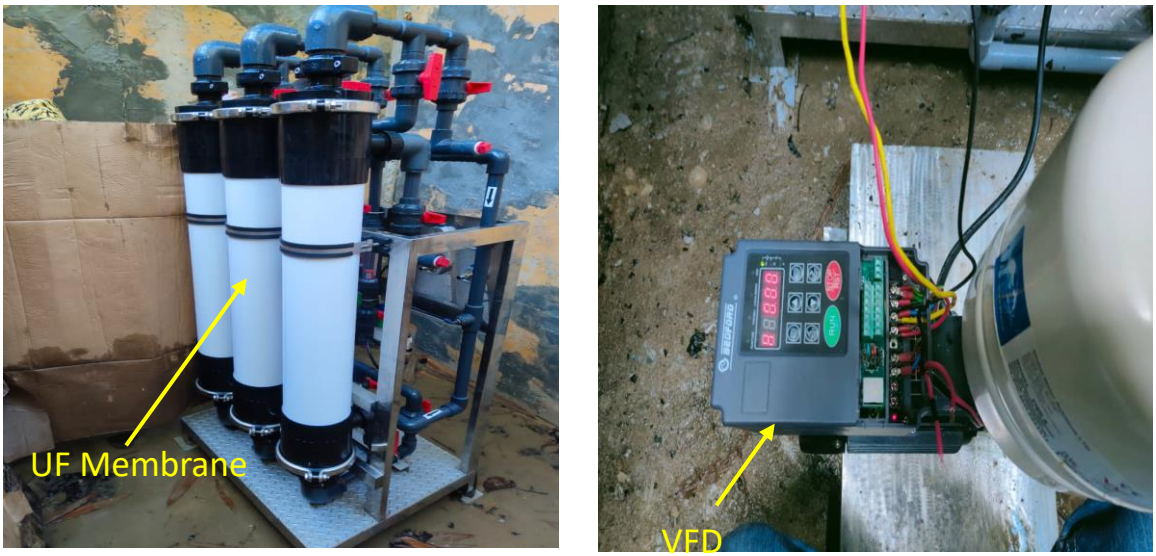


Figure 3.3 (a): UF Membrane and VFD

Figure 3.3 (b): Storage Tank and Level Sensor Set Up

3.4 Research Design for Achieving Specific Objective One

The specific objective of this research is outlined in Chapter 1, where the focus is on evaluating the impact of process control devices on the permeate flux rate [$m^3(sqm)^{-1}$]. The research methodology incorporates factors that influence water output. Figure 3.3 illustrates the steps involved in optimizing the feed pressure.

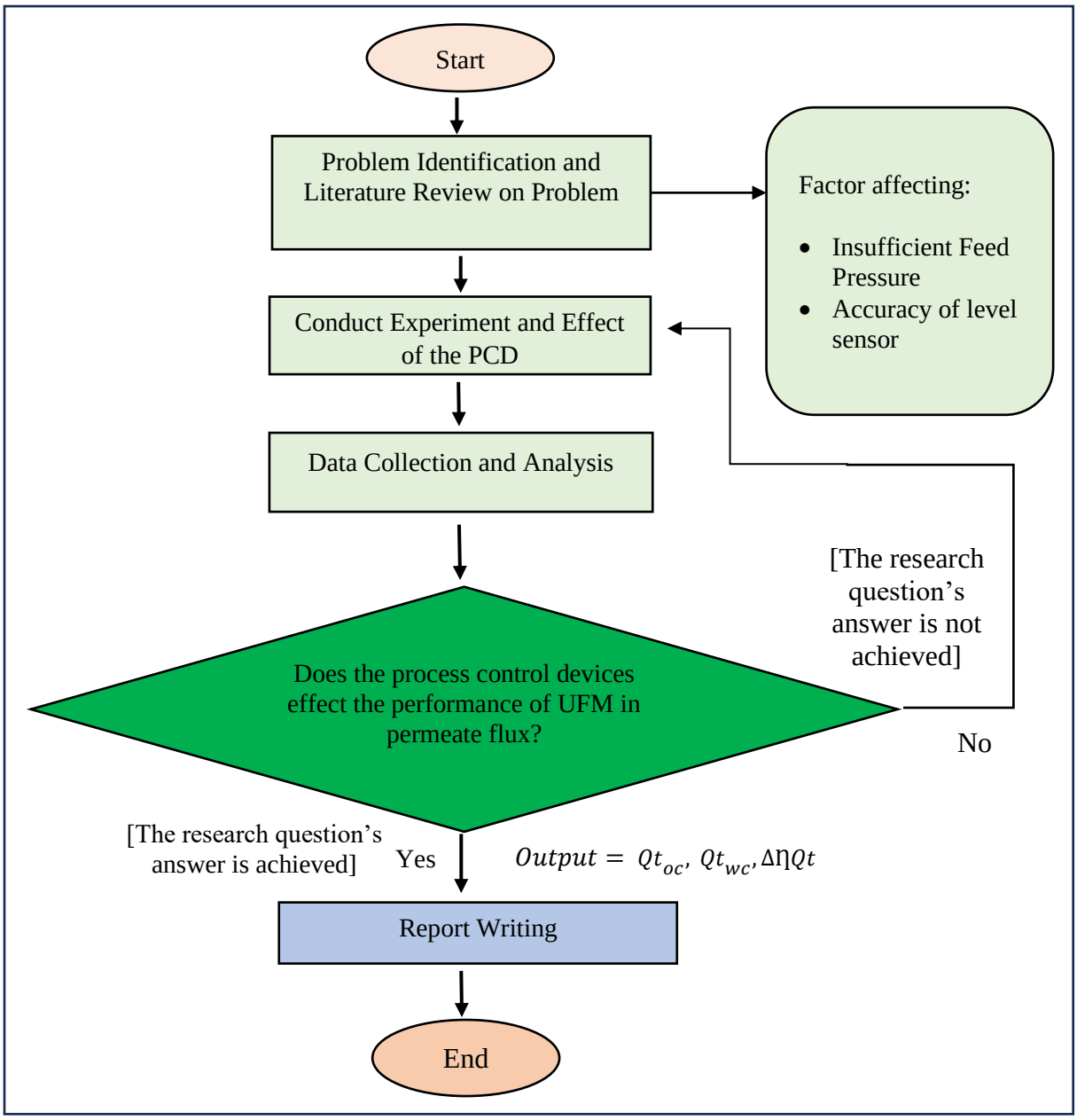


Figure 3. 4: Steps in the Research Methodology for Specific Objective One

3.4.1 Procedure of Conducting Experiment Relating to Objective One

The equipment setup presented in Figure 3.2 has been utilized to conduct the experiment. The equipment for this experiment includes raw water pumps complete with VFD, UFM (UFM), analogue flow meter (AFM), level sensor, buffer tank, clean water storage tank, pressure gauge (PG), and manual valve (MV). Before commissioning and starting up the UFM plant, a standard pre-check activity was performed, as listed below:

i. Ensure all the manual isolation valves (V1, V2, V3, V4, V5, and V6) are fully open
ii. Ensure the manual isolation valves for backwash is closed (V7)
iii. Ensure there is power supply to the VFD pump
iv. Check the parameter in the VFD setting
v. Once item 1 to item 5 have been checked, prepare, record the result as per the table 3.1 and ready for commissioning.

After the process has been checked and aligned, the system is ready for commissioning. Below are the actions taken to achieve objective one:

i. Switch 'ON' the VFD pump
ii. Slowly throttling the VFD to ensure flowrate and pressure are increasing
iii. Check and monitor the analogue flow meter reading and pressure gauge
iv. Ensure water level is increasing and level sensor able to be triggered when water level reaches at the high level
v. Once the system is stable respective to experimental run (refer Table 3.2), monitor and record for each respective output result
vi. Repeat the procedure item 2 to item 5 until it reaches fourteen (14) runs

The experiment has been carried out with a UFM module in accordance with research methodology stated in section 3.4. A UFM module (cylindrical) with membrane

MP4040/0.01 (patented) was used. The surface area of the of this UFM is 7.4 m²; the capacity of the UFM is 80L$(m^2)^{-1}$at nominal pressure at 1.5bar. which contains three medium pressure membrane (2psi) of 40-inch length, 4.0-inch diameter and 0.01µ pore size. According to the objective one (Chapter 1, Section 1.4.i), the experimental setup is depicted in Figure 3.2. This setup has been established to assess the impact of process control devices on the productivity of UFM. The schedule and duration of experiments were recorded in Table 3.1.

Table 3. 1: Distribution of Experimental Runs and Duration of Experiment

Ø	Duration of Experiment	No Experimental Repeat (n)	Total duration of experiment
1	08:00-08:30	8	7 hours a day
2	08:30-09:00	8	
3	09:00-09:30	8	
4	09:30-10:00	8	
5	10:00-10:30	8	
6	10:30-11:00	8	
7	11:00-11:30	8	
8	11:30-12:00	8	
9	12:00-12:30	8	
10	12:30-13:00	8	
11	13:00-13:30	8	
12	13:30-14:00	8	
13	14:00-14:30	8	
14	14:30-15:00	8	

Here (Ø) experimental runs, which is fourteen (14) runs according to Table 3.1. The data collection rate was 0.5 hour per experimental run. The experimental time was 7 hours for conducting 14 experimental runs as shown in Table 3.1. The format of two set of experiment data (with and without process control devices) are presented in Table 3.2.

Finally, experimental data were analyzed by statistical technique, excel software, and paired ‘t' statistic.

Table 3. 2: Data when Plant Operate with and Without Process Control devices

Ø	Q_{in} $m^3.(Ø)^{-1}$ to UFM	Q_{out} $m^3.(Ø)^{-1}$ from UFM	Qcons $m^3.(Ø)^{-1}$ by end users	Water Supply and Consumption Efficiency (ŋ)
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
Ā Q_{PF}			Ā $Q_{PF(cons)}$	Ā(ŋ) =
σ=				Āσ =

Note:

Q_{in} = Water supply to UFM measured by AFM 1 (Figure 3.2)
Q_{out} = Water output from UFM measured by AFM 2 (Figure 3.2)
Q_{cons} = Water consumed by end user measured by AFM 3 (Figure 3.2)

3.4.2 Theoretical Framework Used for Data Analysis of Experiment Relating to Objective One

Mathematical models are required to estimate the permeate flux (Q_{PF}) rate of UFM when plant operate with and without process control devices. The Mathematical models used are listed in **Table 3.3**.

Table 3. 3: Theoretical Framework for to estimate the permeate flux (QPF) rate

Models	Equation Number
Average permeates flux production $\bar{A}(Qp_F) = \frac{\sum_1^{Ø} Qpf}{Ø}$ Here, $\bar{A}(Qp_F)$ is average in permeate flux or product water, Ø is the no of experimental runs or samples. Qp_F is permeate flux or product water.	**(Equation 3.1)**
$\sigma = \sqrt{\frac{\Sigma(Xi-\mu)^2}{Np}}$ σ = Standard deviation Σ = The sum of population standard deviation Np = The size of the population Xi = Each value from the population M = The population mean μ = Mean of population (A. S. Yang and J. L. Morris, 2020)	**(Equation 3.2)**
The impact of process control device on saving total permeate flux of product water $\Delta Q_{PF} = \bar{A}\ Q_{PF(OC)} - \bar{A}\ Q_{PF(WC)}$ Here, ΔQ_{PF} is the amount of permeate flux saved (reduce the wastage) by process control devices. $\bar{A}(Q_{PF})$ is average in permeate flux or product water	**(Equation 3.3)**
Required water outputs from UFM and used by the end users. $Q_{PFt} = Q_{out} \times Ø$ Q_{PFt} is permeate flux or product water.	**(Equation 3.4)**
$\Delta Q_{PFt}\ (\%) = \frac{\Delta QPFt}{Qdpw} 100$ total water demand (Dew) at end users	**(Equation 3.5)**

Total energy consumed by the UFM. *Etave* = E_{ave} x *Qt(oc)*	**(Equation 3.6)**
Efficiency of the UFM. $\eta = \frac{Qcons\ m^3}{\text{QPF}\ m^3} 100$	**(Equation 3.7)**
$\bar{A}(\eta s) = \frac{\sum_1^{\emptyset} \eta s}{\emptyset}$ Here, $\bar{A}(\eta s)$ is average in permeate flux or product water utilization efficiency, Ø is the no of experimental runs or samples.	**(Equation 3.8)**
$t_{st} = \frac{X1-X2}{Sp\sqrt{\frac{1}{N1}+\frac{1}{N2}}}$ X1- average mean of sample 1. N_1 is sample size of 1 X2-average mean of sample 2. N2 is sample size of 2. Sp- Pooled Standard Deviation (M. N. Chen and R. S. Thompson, 2023)	**(Equation 3.9)**
$Sp = \sqrt{\frac{(n_1-1)s1^2 + (n_2-1)S2^2}{N_1+N_2-2}}$ S1=standard deviation of sample 1.0 S2=standard deviation of sample 2.0 (M. N. Chen and R. S. Thompson, 2023)	**(Equation 3.10)**
'df'= N1-N2-2 De-degree of freedom for t-test with pooled variance (M. N. Chen and R. S. Thompson, 2023)	**(Equation 3.11)**

3.5 Hypothesis Test to Evaluate the Contribution of Process Control Devices

The null hypothesis and alternative hypothesis tests can be conducted to evaluate the significance of contribution of process control devices to the productivity of UFM in permeate flux or product water yield (Qp_F).

3.5.1 Null Hypothesis

Ho: $\mu 1 = \mu 2$ at 95% confidence level at (P-value > 0.05). **(Equation 3.12)**

If P-value of mean difference of ΔQp_F with and without process control devices is more than 0.05 (P-value > 0.05), it will indicate that the mean of two data sets is almost equal and has no significant difference. This means the process control devices are not required in WF.

3.5.2 Alternative Hypothesis

H_1: $\mu 1 \neq \mu 2$ at 95% confidence level at (P-value ≤ 0.05). **(Equation 3.13)**

If P-value of mean difference of ΔQp_F with and without process control devices is less than 0.05 (P-value ≤ 0.05), it will indicate that the mean difference of two data sets is not equal and has significant difference. This means that process control devices are required in WF.

3.5.3 Significance T-Test for Evaluating the Impact of Process Control Device on UFM Performance in Permeate Flux Production

T-test is used when the sample size is less than 30. In this case, a t-test is used to evaluate 2 samples data whether the two groups are significantly different in paired measurement. The P-value serves as a metric to assess the significance of process control devices in permeate flux production. If the P-value is greater than 0.05 at a 95% confidence level, it indicates that the contribution of process control devices to permeate flux is not significant. Conversely, if the P-value is less than or equal to 0.05, it suggests that there is a

significant impact of process control devices on permeate flux production. From a paired-samples t-test, P-value can derive from the t score, t-table and normal distribution curve, which is presented in Figure 3.4.

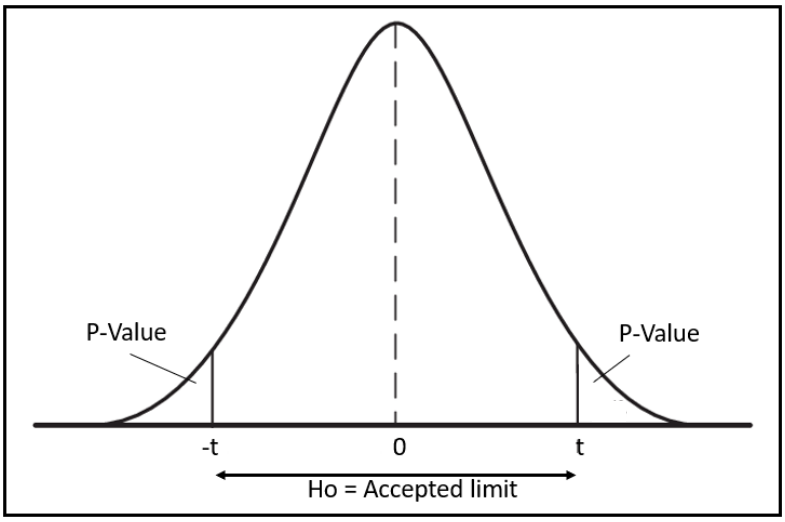


Figure 3. 5: Normal Distribution Curve for 't' test

Null Hypothesis Test:

H_o μ1= μ2 at 95% , the performance of UFM with and without process control devices are the same and do not have a significant difference.

H_1 μ1≠ μ2 at 95%, the performance of UFM with and without process control devices are not the same and have a significant difference.

3.6 Research Design for Achieving Specific Objective Two

The specific objective two of this research is stated in section 1.4(ii) of Chapter 1. The specific objective two is to determine the effect of process control devices on energy consumption rate [kW$(m^3)^{-1}$]. Factors affecting the energy consumption have been included in the research method. The steps shown in Figure 3.5.

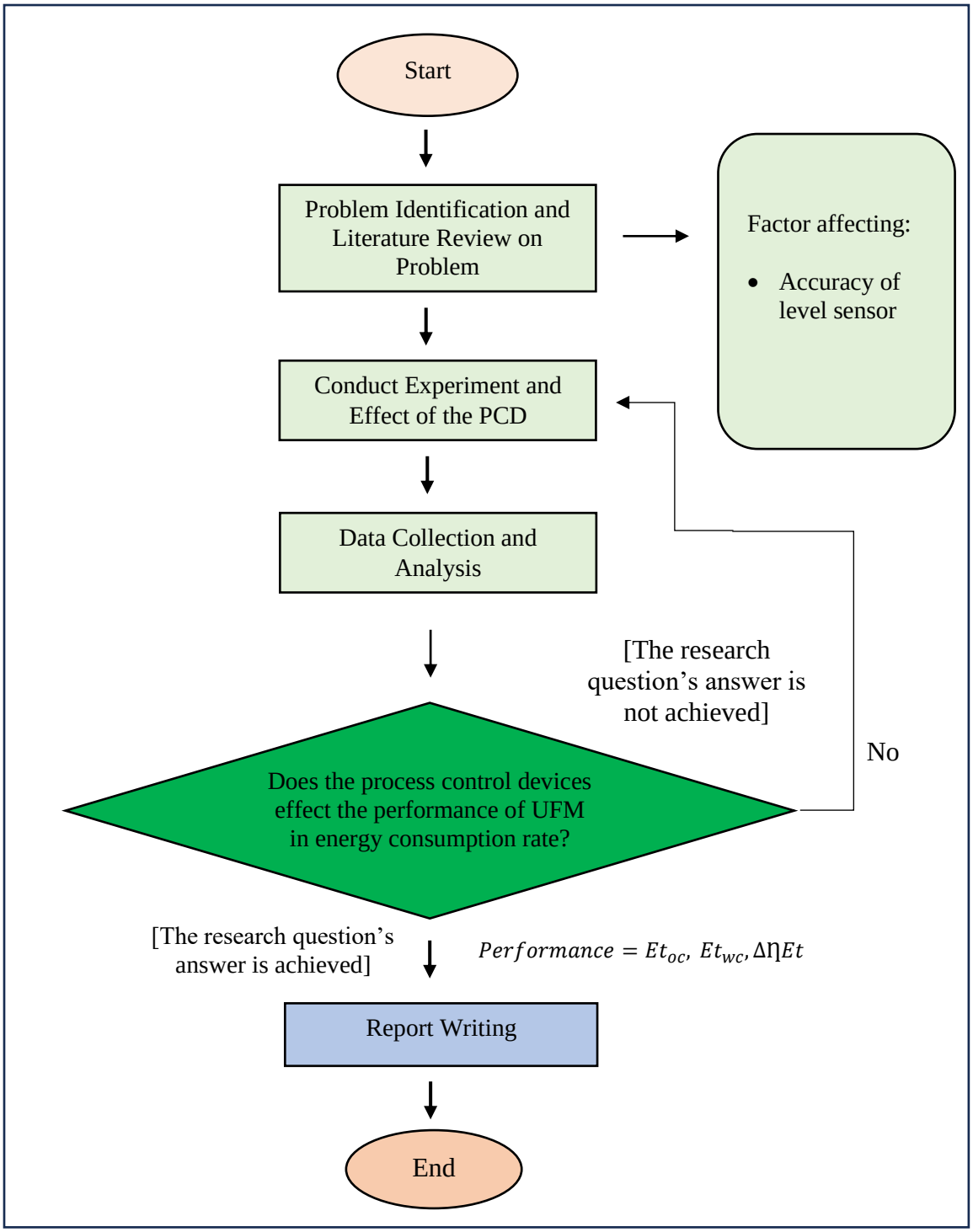


Figure 3. 6: Steps in the Research Methodology for Specific Objective Two

3.6.1 Equipment Set Up for Conducting Experiment

Schematic diagram of equipment used for conducting experiment present in Figure 3.2.

3.6.2 Procedure of Conducting Experiment Relating to Objective Two

The equipment setup depicted in Figure 3.2 has been utilized for conducting the experiment. The experiment's equipment includes raw water pumps equipped with a VFD, UFM, AFM, level sensor, buffer tank, clean water tank, pressure gauge (PG), and manual valve (MV). Before commissioning and start up the UFM plant, a standard pre-check activity has been performed, which listed below:

i. Ensure all the manual isolation valves (V1, V2, V3, V4, V5, and V6) are fully open
ii. Ensure the manual isolation valves for backwash is closed (V7)
iii. Ensure there is power supply to the VFD pump
iv. Check the parameter in the VFD setting
v. Once item 1 to item 5 have been checked, prepare, record the result as per the table 3.1 and ready for commissioning

After the process has been checked and aligned, the system is ready for commissioning. Below are the actions taken to achieve objective one:

i. Switch ‘ON’ the VFD pump
ii. Slowly throttling the VFD to ensure pressure and flowrate is increasing
iii. Check and monitor the analogue flow meter and pressure gauge
iv. Ensure water level is increasing and level sensor able to be triggered when water level reaches at the high level

v. Once the system is stable respective to experimental run (refer table 3.5), monitor and record for each respective output result

vii. Repeat the procedure item 2 to item 5 until it reaches to fourteen (14) runs

The scope of work for objective 2.0 is to evaluate the effect of process control devices on energy consumption rate [kW(m3)$^{-1}$] in permeate flux production. To accomplish this objective, the UFM plant operates in two distinct phases. During the initial phase, the experiment with UFM involves the use of process control devices. Subsequently, in the second phase, the experiment with UFM is conducted without the use of process control devices. The experiment is executed using a UFM module, following the research methodology outlined in section 3.4. A UFM module with membrane MP4040/0.01 was used, which contains three medium pressure membrane (2 psi) of 40-inch length, 4.0-inch diameter and 0.01µ pore size. According to the objective one (Chapter 1, Section 1.4.ii), the experiment has set-up is shown Figure 3.2 to evaluate the effect of process control devices on the energy consumption rate of UFM. The schedule and duration of experiments were recorded in Table 3.4. Here (Ø) experimental runs, which is fourteen (14) runs and estimated by DOE software version 13. The data collection rate is 0.5 hour per experimental run and total experimental time for conducting 14 experimental runs is 7.0 hours. Two set of experiment data (with and without process control devices) are collected and recorded in Table 3.5. Finally, experimental data were analyzed by statistical techniques, excel software and ‘t statistic was used.

Table 3. 4: Distribution of Experimental Runs and Duration of Experiment

Ø*	**Duration of Experiment**	**No Experimental Repeat (n)**	**Total duration of experiment**
1	08:00-08:30	8	7 hours a day
2	08:30-09:00	8	
3	09:00-09:30	8	
4	09:30-10:00	8	
5	10:00-10:30	8	
6	10:30-11:00	8	
7	11:00-11:30	8	
8	11:30-12:00	8	
9	12:00-12:30	8	
10	12:30-13:00	8	
11	13:00-13:30	8	
12	13:30-14:00	8	
13	14:00-14:30	8	
14	14:30-15:00	8	

Table 3. 5: Data when Plant Operate With and Without Process Control devices

Ø	Q_{in} $m^3.(Ø)^{-1}$ to UFM	Q_{out} $m^3.(Ø)^{-1}$ from UFM	[*Eavr(oc)*] $kW(m^3\text{-}Ø)^{-1}$
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
			Eave=
			σ =

Note:

Q_{in} = Water supply to UFM measured by AFM 1 **(**Figure 3.2)
Q_{out} = Water output from UFM measured by AFM 2 (Figure 3.2)
Eavr(oc) = Average energy

3.6.3 Theoretical Framework Relating to The Objective Two

Mathematical models are required to estimate the energy consumption rate of UFM when the plant operates with and without process devices for producing clean water. The Mathematical models used are listed in Table 3.6.

Table 3. 6: Theoretical Framework for Energy Consumption and Efficiency Analysis

Models	Equation Number
Average energy consumption rate over the experimental runs. $Eave = \frac{\sum_1^{Ø} Q_{PF}}{Ø}$ Eave = average energy consumption rate over the experimental runs. Q_{PF} = flowrate in permeate flux Ø = number of experimental runs	**(Equation 3.14)**
The impact of process control device on saving total energy in producing water $\Delta E(m^{3)} = Eave$ (oc) – $Eave$ (wc) ΔE = Amount of energy saved (reduce the wastage) by PCD Eave (oc) = Energy average without PCD Eave (wc) = Energy average with PCD	**(Equation 3.15)**
Required water outputs from UFM and used by the end users. $Eavrt = Eave \times Ø$ Eavrt = Total energy consumption in 14 experimental runs Eave = Energy average Ø = Number of experimental runs	**(Equation 3.16)**
$\bar{A}(ŋs) = \frac{\sum_1^{Ø} ŋs}{Ø}$	**(Equation 3.17)**

Here, Ā(ŋs) is average in permeate flux or product water utilization efficiency, Ø is the number of experimental runs or samples.	
$Q2=\frac{\beta x Water\ Demand,(Qcons)}{No\ of\ experimental\ run\ in\ 7\ hours,(\ \emptyset\ )}$	**(Equation 3.18)**
$N2 = \frac{N1.Q2}{Q1}$	**(Equation 3.19)**
$\eta(E_{ave}) = \frac{Eave(oc)-Eave(wc)}{Eave(oc)}100$	**(Equation 3.20)**

3.7 Hypothesis Test to Evaluate the Contribution of Process Control Devices

The null hypothesis and alternative hypothesis tests can be conducted to evaluate the significance of contribution of process control devices to the energy consumption rat of UFM in permeating flux or product water yield.

3.7.1 Null Hypothesis

Ho: $\mu 3 = \mu 4$ at 95% confidence level at (P-value > 0.05) **(Equation 3.20)**

If P-value of mean difference of ΔE with and without process control devices is more than 0.05 (P-value > 0.05), it will indicate that the mean of two data sets is almost equal and has no significant difference. This means the process control devices are not required in WF.

3.7.2 Alternative Hypothesis

H_1: $\mu 3 \neq \mu 4$ at 95% confidence level at (P-value ≤ 0.05) **(Equation 3.21)**

If P-value of mean difference of ΔE with and without process control devices is less than 0.05 (P-value ≤ 0.05), it will indicate that the mean difference of two data sets is not equal and has significant difference. This means process control devices are required in WF.

3.7.3 Significance T-Test for Evaluating the Impact of Process Control Device On UFM Performance In Energy Consumption

T-test is used when the sample size is less than 30. In this case, a t-test is used to evaluate 2 samples data whether the two groups are significantly different in paired measurement. P-value is a measure to test whether the contribution of Process Control devices in energy consumption is significant. If P-value>0.05 at 95% confidence level, it will be an indicator that the contribution of process control devices in energy consumption is not significant, and vice versa. From a paired-samples t-test, P-value can be derived from the t score, t-table and Normal distribution curve, which is presented in Figure 3.4.

Null Hypothesis test:

H_o $\mu 3 = \mu 4$ at 95% , the performance of UFM in energy consumption with and without process control devices are the same and has no significant difference.

H_1 $\mu 3 \neq \mu 4$ at 95%, the performance of UFM consumption with and without process control devices are not the same and has a significant difference.

3.8 Research Design for Achieving Specific Objective Three

The specific objective three of this research is stated in section 1.4(iii) of Chapter 1. The specific objective three is to optimize the productivity in permeate flux [$m^3(sqm)^{-1}$] and energy consumption rate [$kW(m^3)^{-1}$] permeate flux) of UFM with respect to the feed water pressure and level sensor. The optimization was analysed by using the concept of RSM by Design of Expert Version 13. The steps to achieve this objective are shown in Figure 3.6a and Figure 3.6b.

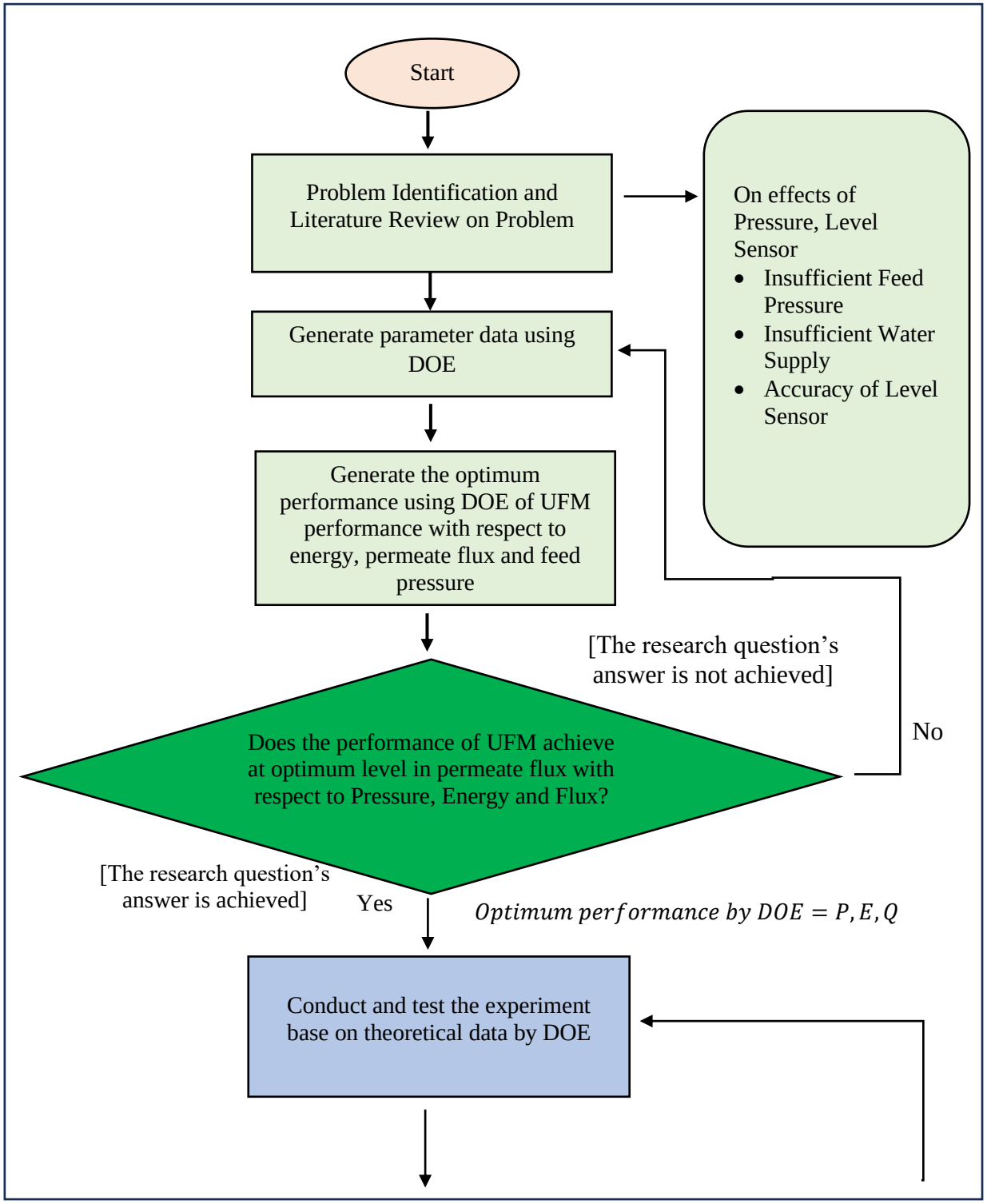


Figure 3. 7 (a): Steps in the Research Methodology for Specific Objective Three

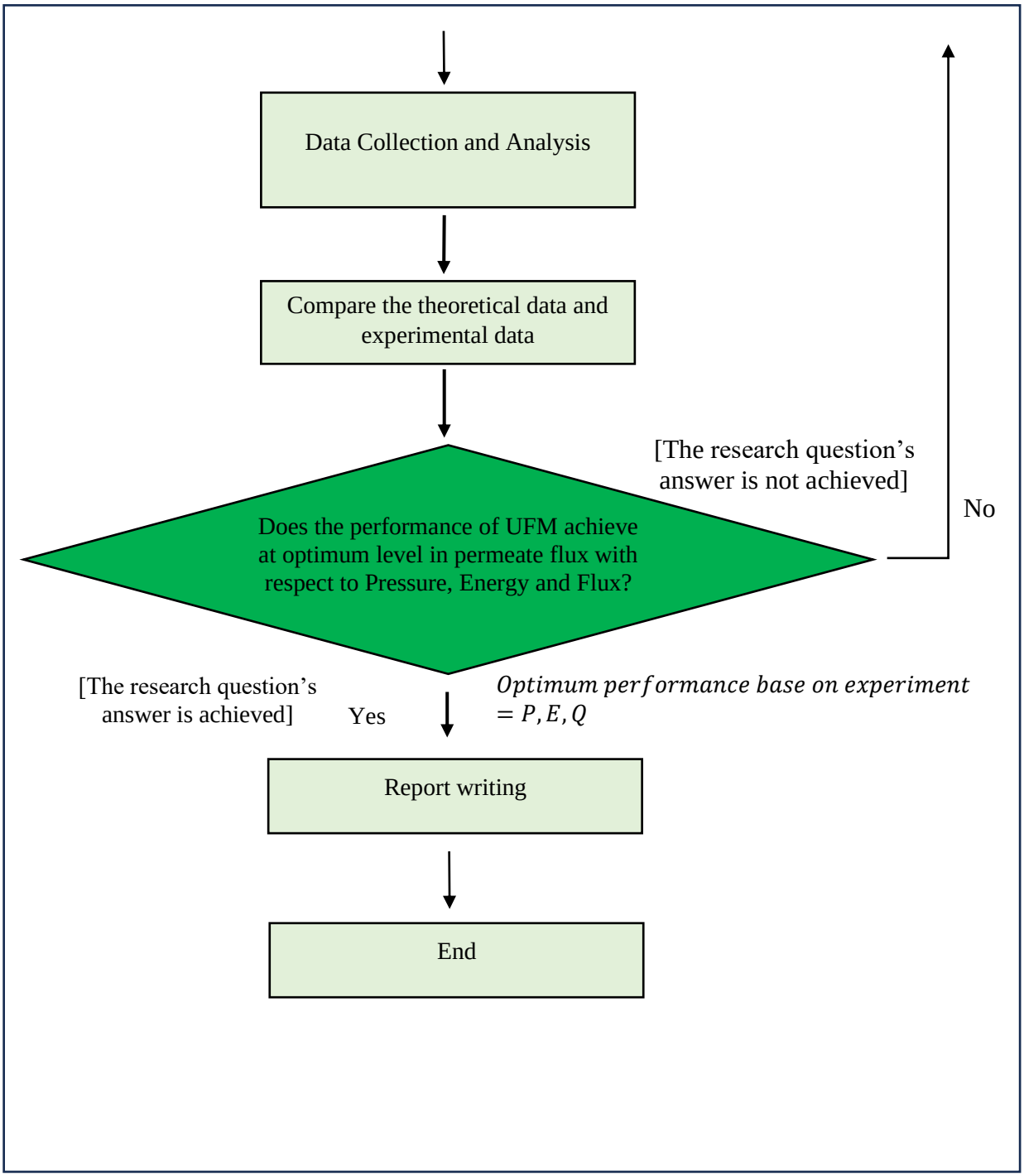


Figure 3. 7 (b): Steps in the Research Methodology for Specific Objective Three

3.8.1 Experimental Set Up Relating to Objective Three

The equipment setup depicted in Figure 3.2 was employed to conduct experiments for achieving objective three. The experimental data, encompassing energy consumption, permeate flux, and feed pressure, were analysed using software to optimize the performance of UFM. The corresponding data recording is presented in Table 3.7**.**

Table 3. 7: Data Table for Effect of Feed Pressure, Flux and Energy Consumption

Standard Order	Experimental Run	Factor 1	Factor 2	Response
		Feed Pressure, bar	Energy Consumption, $kW(m^3)^{-1}$	Flux, $m^3(sqm)^{-1}$

Table 3.7 contains data collection frequency of dependent and independent variables. Later stage, Design Expert Software will be used to analyses the data.

3.8.2 Procedure Conducting Experiment Relating to Objective Three

The parameter data for independent and dependent variables are generated using Design of Experiments (DoE) software, version 13. The data will be used to assess the

optimal operation in Design of Experiments (DoE). Input variables, such as feed pressure and energy, and output variables, specifically permeate flux, will be examined in the context of DoE. Then, run the simulation of DOE. A comprehensive understanding of these variables and their ranges ensures that input adjustments, particularly in feed pressure and energy, result in the desired final design for permeate flux. The establishment of input-output models is crucial for acquiring knowledge. The creation of mathematical linkages between Critical Process Parameters (CPPs), Critical Material Attributes (CMAs), and Critical Quality Attributes (CQAs) defines the design space. Consequently, a thorough comprehension of the process is secured, leading rationally to the achievement of a Maximum Target Desired Profile output (MTDP). The data will undergo analysis using 5-level fractional factorial designs. There are 8 steps in establishing the optimum operation as listed below:

Step 1: The variable (Feed Pressure and Energy) and response (Permeate Flux) selection is decided based on the DoE objectives and should provide the entire design as executable and suitable for achieving its scope. This implies that numeric or categorical factor types and their levels, i.e., the ranges within the design, are chosen accordingly.

Step 2: The value of five levels ($-\alpha$, -1,0,1, α) is determined to justify the range between each level.

Step 3: The choice of an experimental design, including Response Surface Technique and Central Composite Design, is contingent upon the objectives of Design of Experiments (DoE). Depending on whether the aim is screening, characterization, or optimization of processes and formulations, various design types—such as factorial and mixed designs—can be considered.

Additionally, decisions regarding randomization, blocking, and replication must be carefully deliberated.

Step 4: The fourth step involves comparing generic data with experimental data. Design-of-Experiments (DoEs) excel in identifying outliers, which can arise from inadequately conducted trials.

Step 5: The fifth step involves analysing the results, utilizing tools such as ANOVA and graphical methods to identify the main effects and interactions of significant components. The analysis extends beyond mere statistical evaluation; it includes a comparison with existing theories, resulting in the development of practical process knowledge.

Step 6: The use and interpretation of the results are crucial at this stage. The evaluation of the Design of Experiments (DoE) outcome plays a pivotal role in scientifically informed decision-making for subsequent steps. This includes conducting confirmatory runs, modifying designs, or continuing with scale-up and technology transfer initiatives. The success of these seven processes is intricately tied to the construction of an environment that can facilitate the flawless execution of the DoE.

Step 7: In the seventh step, examine the correlation and intercept between the input variables, specifically Feed Pressure and Energy.

Step 8: Compile a comprehensive report and graph that encompass run, projected, and actual results. Generate a 3D graph featuring optimal values for specific variables such as feed pressure and energy, along with permeate flux, to achieve peak operational performance. Visualize the Central Composite Design (CCD) as a crucial step in optimizing performance generation.

Use the DOE data and apply the DOE data result on site to prove the theory applied is correct. Monitor and record the optimum point or optimum operation of the process on site. Compare the data between the theoretical data and the experiment data

3.9 Designing Model Optimization and Validation

The process of model optimization and validation reveals that the coefficient estimations accurately reflect the objective equation. In order to assess model optimization, it is essential for the factors to demonstrate a significant value according to the objective equation, as outlined below:

$$Y = A + \alpha 1 + \alpha 2 + \alpha 3 = \text{Intercept} - A - B - C \qquad \textbf{(Equation 3.22)}$$

Parameters Checking

A is intercept of regression, B and C are variables.

α1, α2, α3 are coefficient of variables which associated with the P-value (also known as elasticity of outputs)

If the P-value is less than or equal to the significance level, it can be concluded that there is a statistically significant association between the response variable and the term.

P-value > α: The association is not statistically significant.

If the P-value is greater than the significance level, it cannot be concluded that there is a statistically significant association between the response variable and the term. The data may refit the model without the term.

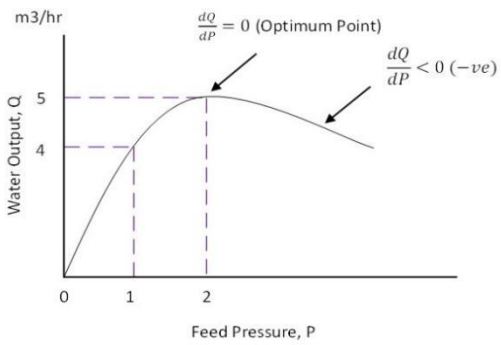
3.10 Research Variables

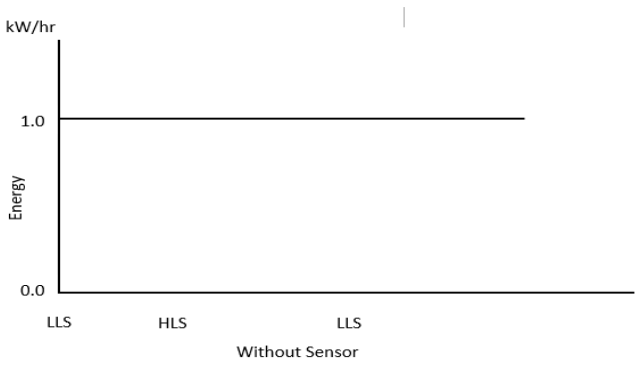
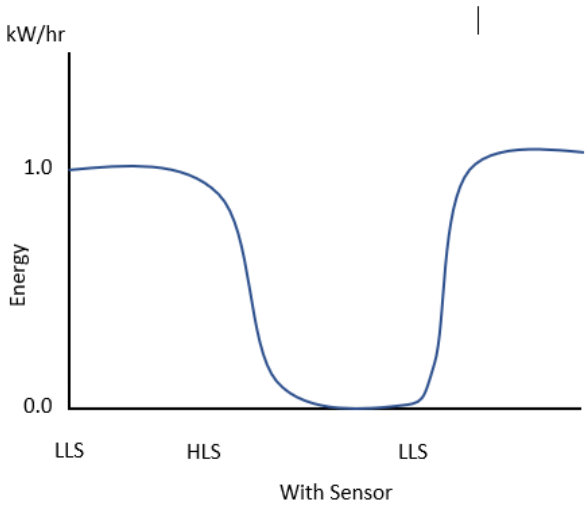
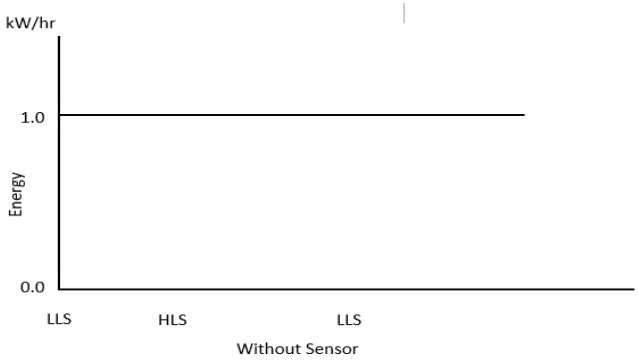
In this study, we examine the variables that comprise both the dependent and independent variables. The definition of variables and its character is presented in Table 3.8 and Table 3.9.

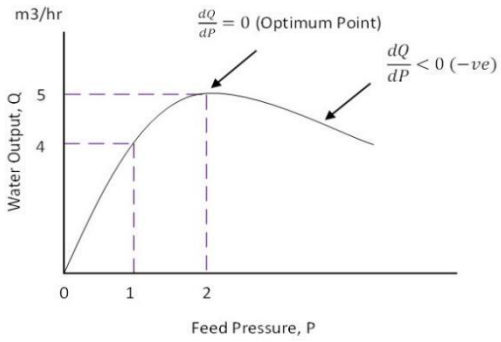
Table 3. 8: List of Variables and Definitions for Ultrafiltration Performance

Research Variables	
Output	
Dependent Variable	**Definition of Variable**
Permeate flux	It measures the capacity of water output (Cui et al., 2010)
Independent Variable (Descriptive Variable)	**Definition of Variable**
Input	
Feed Pressure	To determine the effect of feed pressure and its optimum to ensure the optimization of the plant/system capacity (Cui et al., 2010) (Jadhao & Dawande, 2012)
Energy Consumption	It measures the amount of energy usage (Prisciandaro et al., 2019)

Table 3. 9: List of Independent and Dependent Variables Used

Research Variables		
Process	**Dependent Variable**	**Independent Variable**
Objective 1 **(with process control devices)**  	Permeate flux, Q • To analyse the effect of productivity in permeate flux	Experimental Run

Objective 1 **(without process control devices)**  	Permeate flux, Q To analyse the effect of productivity in permeate flux	Experimental Run
Objective 2 **(with process control devices)**  	Energy Consumption • To analyse the effect of energy consumption rate	Experimental Run
Objective 2 **(without process control devices)**  	Energy Consumption • To analyse the effect of energy consumption rate	Experimental Run

Objective 3  	To determine the optimal performance of UFM Permeate flux	To determine the optimal performance of UFM Feed Pressure, • To determine the process control optimization under the effect of feed pressure ii. Energy Consumption To determine the optimal of the energy consumption rate

3.11 Data Analysis Method

Before collecting the actual data, based on physical or site measurements, the data will be analyzed using Microsoft Excel. Subsequently, the data obtained (as detailed in Chapter 4) will undergo analysis using Design of Expert (DOE) software, specifically version 13. The data computed in DOE will then be further analyzed using control charts as a basis. The control charts will be established with ± 3σ limits, assuming that the experimental data follows a normal distribution. To validate the optimum performance of the UF Membrane, the data will be tested on the actual site, aligning with the information derived from the software analysis for justification.

3.12 Significance T-Test for Evaluating the Impact of Process Control Device on UFM Performance in Optimum Performance

T-test is used when the sample size is less than 30. In this case, a t-test is used to evaluate 2 samples data whether the two groups are significantly different in paired measurement. P-value is a measure to test whether the contribution of Process Control devices in energy consumption is significant. If P-value>0.05 at 95% confidence level, it will be an indicator that the contribution of process control devices in overall performance either the feed pressure to permeate flux and energy consumption to permeate flux are not significant, and vice versa. From a paired-samples t-test, P-value can be derived from the t score, t-table and Normal distribution curve, which is presented in Figure 3.4.

Null Hypothesis test:

H_o $\mu 5 = \mu 5$ at 95%, the performance of UFM in energy consumption with and without process control devices are the same and has no significant difference.

H_1 $\mu 6 \neq \mu 6$ at 95%, the performance of UFM consumption with and without process control devices are not the same and has a significant difference.

3.13 The Conceptual Input-Outputs Model of UFM in Producing Permeate Flux

Energy and feed pressure are the potential inputs for producing product water (permeated flux) by UFM.). The conceptual model for input-output of UFM in producing permeate flux is presented in Figure 3.7.

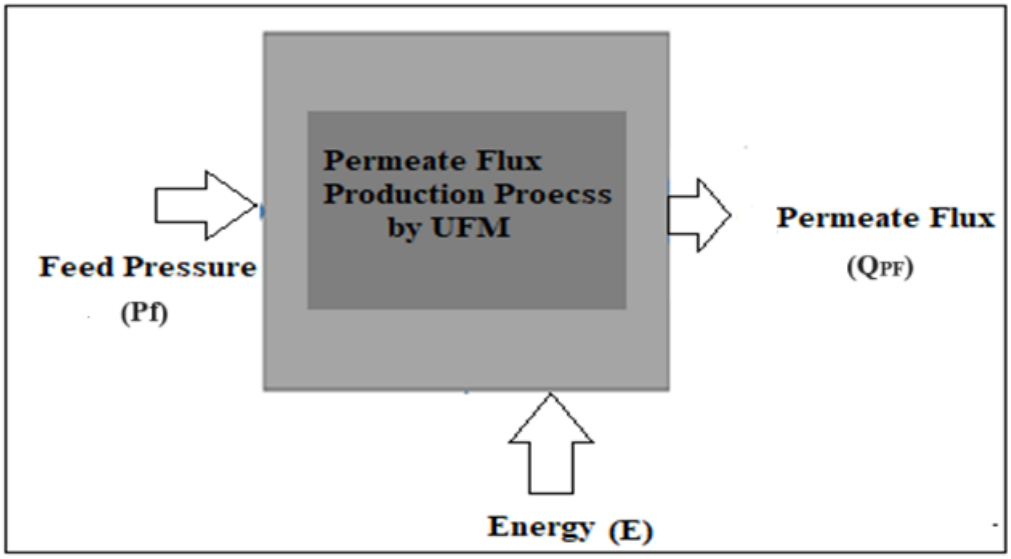


Figure 3. 8: Input-Out Model of UFM in producing permeate flux

Feed pressure (in bars) is crucial in overcoming the resistance of the UFM to achieve the optimal permeate flux. Energy consumption rate (E), measured in kW(m3)$^{-1}$, is the rate at which UFM produces the optimum permeate flux. Permeate flux depends on both feed pressure (in bars) and energy consumption rate. The performance of the UFM can be accurately represented by the following model:

$$\text{Performance} = \text{P, E, Q} \qquad \textbf{(Equation 3.23)}$$

Figure 3.7 shows that the permeate production process is a non-linear process which can be expressed mathematically by Equation 3.24.

$$Q_{permeate\ flux} = A_O (Pr)^{\alpha} . E^{\beta} K \qquad \textbf{(Equation 3.24)}$$

The linear form of Equation 3.23 is presented in Equation 3.25.

$$\log(Q_{permeate\ flux}) = \log A_O + \alpha \log(Pr) + \beta \log(E) + \log K \qquad \textbf{(Equation 3.25)}$$

Where, A_O is the intercept of the line at y-axis, the coefficient of Pr is ‘α’ which contributes to Q_{PF} ($Q_{\text{permeate flux}}$) yield. The coefficient of E is ‘β’ which contributes to Q_{PF} yield. The regression term error is represented by ε , and K is constant.

3.14 Chapter Summary

This chapter outlines the research methodology essential for achieving the research goal. The study at hand involves experimental research, conducted to enhance the performance of UFM in producing clean water. The first specific objective of the experiment was to assess the impact of process control devices on the UFM's performance in terms of permeate flux yield and efficiency. The effect of the process control device is quantified using the t-statistic in the significance test (α=0.05). The second specific objective of the experiment aimed to determine the influence of process control devices on the UFM's performance concerning energy consumption, permeate flux, and efficiency. Like the first objective, the effect of the process control device is measured using the t-statistic in the significance test (α=0.05). The third specific objective of this experiment focused on optimizing the UFM's performance in terms of permeate flux, energy consumption rate, and feed pressure. The necessary mathematical model, experimental setup, and data analysis method are presented in this chapter. The chapter concludes with a detailed description of the experimental setup.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the objectives finding and result which are pertinent to the aim and objectives of this study. The results and discussion sections in this chapter are divided into three main stages which correspond to the devised objectives as depicted by Figure 3.1 in Chapter 3.

This research aims to evaluate and optimize the performance of an UFM system by focusing on three main objectives. First, it examines the effect of process control devices on the permeate flux rate by comparing the UFM plant's operation with and without these devices. Second, it assesses the impact of these process control devices on the energy consumption rate using a similar two-phase approach. Finally, it seeks to optimize UFM performance by adjusting and analyzing feed water pressure, energy consumption rate and permeate flux. This comprehensive methodology aims to enhance the overall efficiency and productivity of the UFM system.

4.2 Experiment Without Process Control Devices for Permeate Flux Production

One set data were collected from the 14.0 experimental runs, which are presented in Table 4.2. Table 4.2 is developed in accordance with the Table 3.2 and estimate of Equation 3.7 for the efficiency of Q_{PF}.

Table 4. 1: Data when Plant Operate without Process Control Devices at RPM 1500

Ø	Q_{in} $m^3.(Ø)^{-1}$ to UFM	Q_{out} $m^3.(Ø)^{-1}$ from UFM	Q_{cons} $m^3.(Ø)^{-1}$ by end users	Water Supply Consumption Efficiency $ηoc_{(QPF)}$
1	1.0	1.0	0.6	0.60
2	1.0	0.95	0.6	0.63
3	1.0	0.95	0.65	0.68
4	1.0	1.0	0.65	0.65
5	1.0	0.90	0.7	0.77
6	1.0	0.95	0.75	0.78
7	1.0	1.0	0.75	0.75
8	1.0	1.0	0.8	0.8
9	1.0	0.95	0.8	0.84
10	1.0	0.90	0.8	0.88
11	1.0	0.95	0.75	0.78
12	1.0	0.90	0.75	0.83
13	1.0	1.0	0.70	0.70
14	1.0	0.97	0.65	0.67
X_1 = Ā Q_{PF} (oc) = 0.958			Ā Q_{PF} (cons)=0.710	Ā(ηoc) =0.743 (74.3%)
S_1 = Āσ$_{oc}$ = 0.038				Āσ$_{oc}$ =0.087

Here,

Q_{in} = Q1
= Design capacity = $1.0m^3.(Ø)^{-1}$
= Water supply to UFM measured by AFM 1 (Figure 4.1)

Q_{out} = Water output from UFM measured by AFM 2 (Figure 4.1)
Q_{cons} = Water consumed by end user measured by AFM 3 (Figure 4.1)

N1 = Pump speed design capacity = RPM 1500

Ā Q_{PF} (oc) = Average permeate flux without process control devices

Ā Q_{PF} (cons) = Average permeate flux consumes by end users

Ā(ηoc) = Average water supply efficiency without process control devices

Āσ$_{oc}$ = Average standard deviation without process control devices

$η_{QPF}$ = Efficiency of UFM in permeate (water) production and supply, The efficiency of Q_{PF} is estimated from Equation 3.7.

Table 4.2 shows the permeate flux production and supply to the end users. Here, Ā $Q_{PF\,(OC)}$ is average permeate flux supply to the end users, which was estimated from Equation 3.1. σ_{oc} is standard deviation of Q_{PF} supply to the end users. The σ_{oc} is estimated from Equation 3.2. The Q_{PF} efficiency was estimated from Equation 3.7. The characteristics of permeate flux production of UFM are also presented in Figure 4.1.

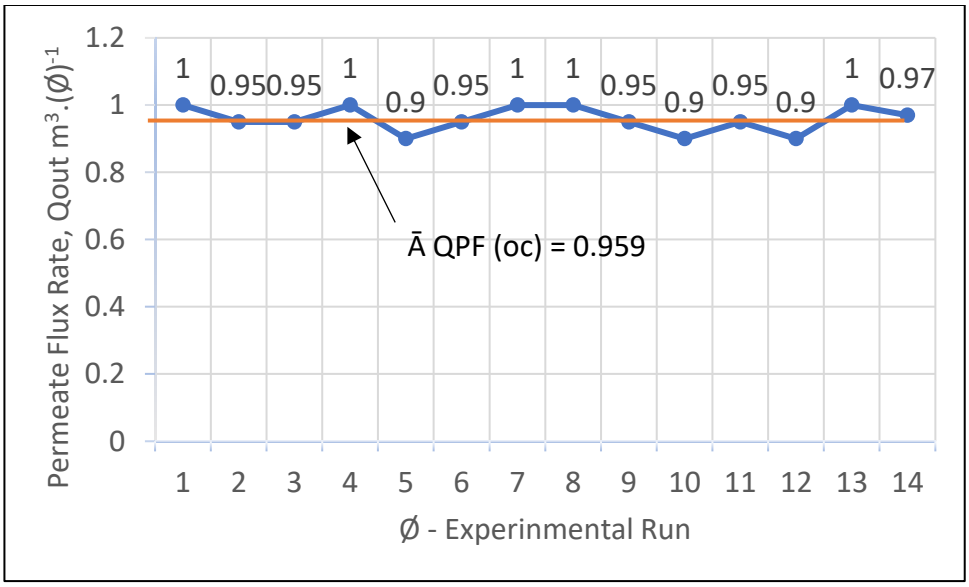


Figure 4. 1: Permeate Flux production Yield without Process Control Devices

Figure 4.3 and Table 4.2 demonstrate the outcomes of the experiments. The average permeates flux supply to end users is 0.959 $m^3(Ø)^{-1}$, which is achieved at standard deviation of 0.038 at a water consumption efficiency of 74.3%.

4.3 Experiment with Process Control Devices for Permeate Flux Production

The purpose of this section was to conduct an experiment aimed at determining the permeate flux production rate when the plant is operated with process control devices. The experimental setup comprises a UFM, a feed water pump, a product water storage tank, a VFD, and water level sensors. The storage tank has a capacity of 2.0 m^3 and is positioned at

a height of 1.8 m, with a water overflow pipe installed at the same height. Two level sensors were placed at different levels within the tank, one at the 1.8 m high level (HL) and the other at the 0.2 m low level (LL). The water tank is connected to the end users of water. Details of the experimental run, including the duration of the experiment and the experimental time, can be found in **Table 4.2**. The experimental data, presented in **Table 4.2**, were developed based on the information provided in **Table 3.2** and **Table 4.1** is developed in accordance with the **Table 3.2** and estimate of **Equation 3.7** for the efficiency of Q_{PF}.

Table 4. 2: Data when Plant Operate with Process Control Devices at RPM 1170

Ø	Q_{in} $m^3.(Ø)^{-1}$ to UFM	Q_{out} $m^3.(Ø)^{-1}$ From UFM	Qcons $m^3.(Ø)^{-1}$ by end users	Water Supply Consumption Efficiency (ŋwc)
1	0.78	0.41	0.38	0.93
2	0.78	0.51	0.45	0.88
3	0.78	0.63	0.55	0.87
4	0.78	0.8	0.75	0.94
5	0.78	0.9	0.81	0.90
6	0.78	0.92	0.88	0.96
7	0	0.92	0.88	0.96
8	0.78	0.85	0.81	0.95
9	0.78	0.83	0.72	0.87
10	0.78	0.72	0.67	0.93
11	0.78	0.65	0.61	0.94
12	0.78	0.61	0.53	0.87
13	0.78	0.53	0.49	0.92
14	0.78	0.39	0.36	0.92
$X_2 = \bar{A}\ Q_{PF}$ (wc) = 0.691			0.635	$\bar{A}$(ŋwc) =0.917 (91.7%)
$S_2 = \bar{A}\sigma_{oc}$ = 0.185				$\bar{A}\sigma_{wc}$ =0.033

Here,

Q_{in} = Q2

= Required water production to meet the water demand at zero wastage

(only 10.0m3 for 7 hours at a β value 1.1),

= Water supply to UFM measured by AFM 1 (Figure 4.1)

$= 0.78m^3.(Ø)^{-1}$

Q_{out} = Water output from UFM measured by AFM 2 (Figure 4.1)

Q_{cons} = Water consumed by end user measured by AFM 3 (Figure 4.1)

$\bar{A}\ Q_{PF}$ (wc) = Average permeate flux with process control devices

$\bar{A}(\eta_{wc})$ = Average water supply efficiency with process control devices

$\bar{A}\sigma_{wc}$ = Average standard deviation with process control devices

η_{WC} = efficiency of Q_{PF} is estimated from Equation 3.7.

Table 4.3 shows the permeate flux production and supply to the end users. Here, $\bar{A}$ Q_{PF} (wc) is average permeate flux supply to the end users, which was estimated from Equation 3.1. σ_{oc} is standard deviation of permeate flux supply to the end users. The σ_{wc} is estimated from Equation 3.2. The efficiency in energy consumption was estimated from Equation 3.7. The characteristics of permeate flux production of UFM are presented in Figure 4.2.

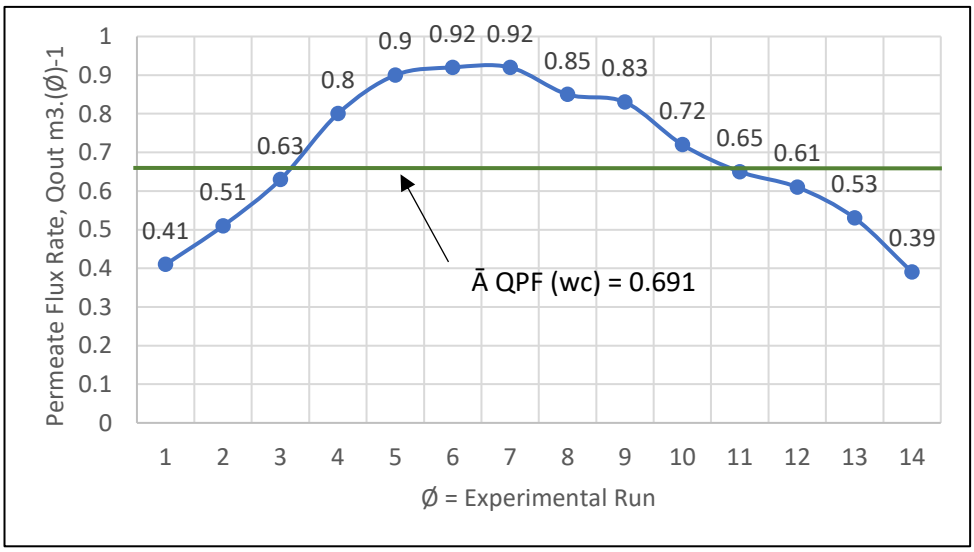


Figure 4. 2: Permeate Flux production Yield with Process Control Devices

Figure 4.2 and **Table 4.2** demonstrate the outcomes of the experiments. The average permeate flux supply to the end users is 0.691 $m^3(Ø)^{-1}$, which is achieved at standard deviation of 0.185 and water consumption efficiency of 91.7%.

Equation 4.1 is used to estimate the demand of water to be produced at zero wastage. To address it, a VFD for speed control of the pump and water level sensors in the water tank have been used. The required water production rate to meet the water demand (Q2) at zero waste (only 10.0 m^3 for 7 hours at a β value 1.1).

$$Q2 = \frac{\beta x Water\ Demand}{No\ of\ experimental\ run\ in\ 7\ hours} = \frac{1.1x10.0}{14.0\ hours} \qquad \textbf{(Equation 4.1)}$$

$$= 0.78m^3.(Ø)^{-1}$$

To evaluate the required pump speed (RPM) in order to produce water supply 0.78 m^3. $(Ø)^{-1}$, the required pump speed, N2 is presented in Equation 4.2.

$$\frac{Q2}{Q1} = \frac{N2}{N1} \qquad \textbf{(Equation 4.2)}$$

Here, Q_{in} = Q1 = 1.0 $m^3.(Ø)^{-1}$. Q2=0.78 $m^3.(Ø)^{-1}$. Ø=14, N1=1500. N2 is required speed for producing only 0.78 m^3. $(Ø)^{-1}$.

$$N2 = \frac{\mathrm{N1.Q2}}{\mathrm{Q1}} = \frac{1500x0.78XØ}{14} = \frac{1500\mathrm{x}0.78\mathrm{x}14}{14} = \mathrm{RPM1170} \qquad \textbf{(Equation 4.2a)}$$

4.4 Evaluation of the Impact of Process Control Devices on UFM's Productivity in Permeate Flux Production

The impact of using process control devices on the performance of Permeate Flux production in Ultrafiltration Modules (UFMs) was assessed at a 95% confidence level (significance level α = 0.05). The measurement of this impact utilized the Permeate supply

from the product water tank. Reference to Table 4.1 and Table 4.2 reveals that the average permeate flux supply to end-users was 0.917 $m^3(Ø)^{-1}$ without process control devices, and 0.691 $m^3(Ø)^{-1}$ with process control devices. The evaluation of the impact of process control devices on UFMs in permeate flux production was conducted by estimating the **Equation 3.3**.

$$\Delta Qp_F = \bar{A}Qp_{F(oc)} - \bar{A}Q_{PF(wc)} \qquad \textbf{(Equation 4.2b)}$$

$$\Delta Qp_F = 0.917\text{-}0.691 = 0.226\ m^3.\ (Ø)^{-1} \qquad \textbf{(Equation 4.2c)}$$

Here, ΔQp_F is the amount of permeate flux saved by process control devices. The Equation 3.4 was estimated to determine total permeates flux saving in 14 experimental runs, which is presented in Equation 4.3.

$$\Delta Qpwt = Øx\ \Delta Qp_F = 14x0.226 = 3.16\ m^3 \text{ a day} \qquad \textbf{(Equation 4.3)}$$

The percentage of savings in relation to the total water demand (Qd_{PF}) at end users attributed to the contribution of process control devices, can be estimated using Equation 3.5, which is further presented in Equation 4.4.

$$\Delta Q_{PF}t\ (\%) = \frac{\Delta QPF}{QdPF} 100 \qquad \textbf{(Equation 4.4)}$$

$$= \frac{3.16}{10} = 31.6\%$$

The contribution of process control devices in terms of efficiency of water output, Q_{PF} at end users can be estimated from the Equation 3.7, which is presented in Equation 4.5.

$$\Delta\eta = [\eta wc - \eta oc] \qquad \textbf{(Equation 4.5)}$$

$$\Delta\eta = 0.917\text{-}0.743 = 0.174\ (17.4\%)$$

The findings presented in Equation 4.2**,** Equation 4.3**,** and Equation 4.4**,** demonstrate that there is a positive difference between these two processes. The process control devices have significantly contributed to saving productivity in permeate flux consumption by 3.16

$m^{3,}$ a day, or 31.6%. In addition to this, the water consumption efficiency ($\Delta\Pi$) has increased by 17.4%. Equation 4.3**,** Equation 4.4**,** and Equation 4.5 further demonstrate that the process control devices have made a positive contribution to the performance of UFM in permeate flux production. In light of these findings, the research question is 'whether the contribution of process control devices is significant?'

4.5 Hypothesis Test to Check Whether Process Control Devices Has a Significant Impact on The UF Performance in Producing Permeate Flux

To test the hypothesis, models stated in sections 3.5 have been used. This test involved paired-samples t-test at 95% significant level. S_p is calculated from equation 3.10 by using data from Table 4.2 and Table 4.3. The estimated value of S_p is: 0.333 (refer to appendix J).

Here, from Table 4.2

S_1=standard deviation of sample means 1 = 0.038

X_1-average of sample mean 1 = $\bar{A}(Qp_F)wc$= 0.958

N_1 is sample size = 14.

From Table 4.2

S_2=standard deviation of sample means 2= 0.185

X_2-average of sample mean 2 = $\bar{A}(Qp_F)_{OC}$= 0.691

N_2 is sample size = 14.

The degree of freedom can be estimated from Equation 3.11.

df= $(N_1+ N_2–2)$ = 26.

The ‘t_{est}’ is estimate from Equation 3.9.

The estimated value of t_{est} = ±2.12 (Detail estimate is attached in appendix K) is less than critical value t_c = ±2.056 (t table is attached in appendix N), which is P-value < 0.05. The statistical data is presented in Figure 4.3.

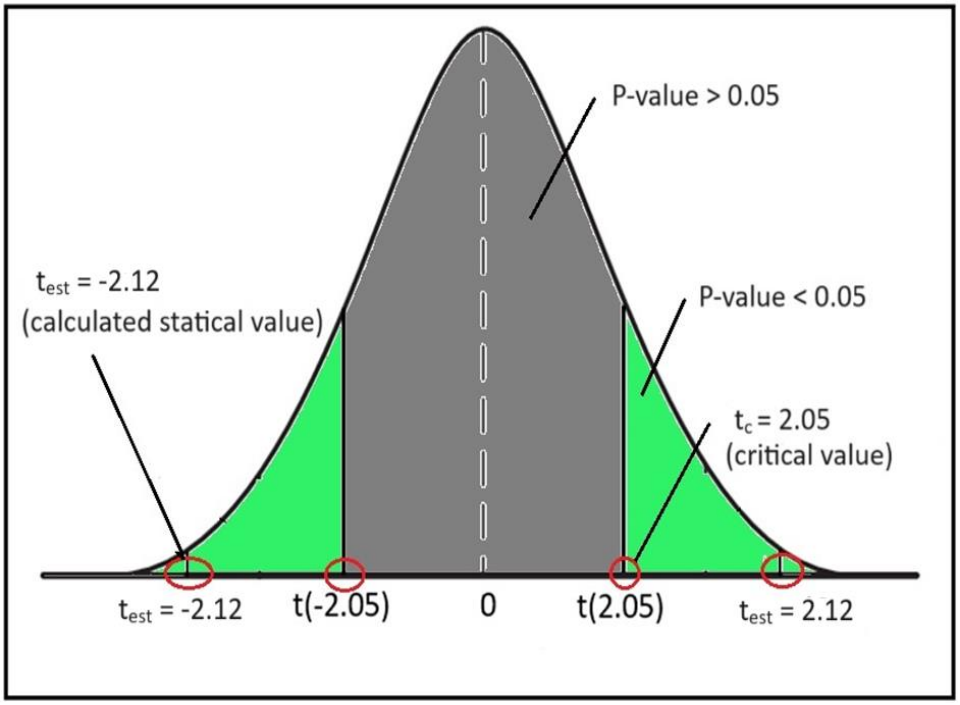


Figure 4. 3: ‘t’ score for hypothesis test with mean value of average water consumption rate

Figure 4.3 demonstrates that the estimated ‘t_{est}’ value is less than the critical value t_c (P-value <0.05). With these findings, the study provides sufficient information to assert that the means of the two sets of data are not equal, leading to the rejection of the null hypothesis (H_o). Conversely, the alternative hypothesis (H_a) is accepted. This suggests that process control devices have significantly (P-value <0.05) contributed to the increase of permeate flux of UFM in producing permeate flux. In light of this discovery, the study concludes that the impact of process control devices on the performance of UFM in producing permeate flux is substantial, and these devices are deemed necessary in water filtration processes.

4.6 Findings and Answer to The Research Question One

The findings from data analysis of experiments related to objective one are presented in Table 4.1, Table 4.2, Figure 4.1, and Figure 4.2. These findings demonstrate that process control devices have a significant impact on the performance of UFM in permeate flux yield. Specifically, experiments were conducted to assess the influence of process control devices on permeate flux. The experimental data with and without process control devices were analysed and tested with the 'paired test' at 95% confidence level. The findings revealed that process control devices have significantly impacted the permeate flux, which resulting 31.6% saving the water consumption of permeate flux. This contribution is deemed significant, at P-value less than 0.05. This outcome, aligned with the first research objective, affirms the successful achievement and resolution of research question one.

4.7 Conducting Experiment and Research Findings Relating to Objective Two

The experiment was conducted using a UFM module in accordance with the research methodology outlined in Section 3.4. In alignment with Objective One (Chapter 1, Section 1.4.ii), the experiment was designed to assess the impact of process control devices on the performance of UFM in terms of energy consumption rate [kW$(m^3)^{-1}$ he methods for conducting the experiment, data collection, and data quality improvement are described in Section 3.2, Section 3.3, Section 3.6, and Section 3.11 of Chapter 3.0. Figure 4.2 illustrates the experimental setup related to Objective One.

4.8 Experiment Without Process Control Devices for Measuring Energy Consumption Rate

This section presents the results of an experiment conducted to determine the permeate flux production rate when the plant operates without process control devices. The key equipment used in this study includes the UFM plant with process control devices and a product water storage tank. The water storage tank had a capacity of 2.0 m^3, and was connected to water end users. The pump had a capacity of 2.0 m^3 $(hr)^{-1}$ at 1500 RPM. Water consumption by end-users was recorded and estimated at 10.0 m^3 for 7 hours a day, from 8:00 am to 3:00 pm. Data were collected from 14 experimental runs, resulting in two sets of data, which are presented in Table 4.5. This table is developed in accordance with Table 3.5.

Table 4. 3: Energy Data when Plant Operate without Process Control Device at RPM 1500

Ø	Q_{in} $m^3.(Ø)^{-1}$ to UFM	Q_{out} $m^3.(Ø)^{-1}$ from UFM	[Eave(oc)] $kW(m^3\text{-}Ø)^{-1}$
1	1.0	1.0	0.54
2	1.0	0.95	0.56
3	1.0	0.95	0.55
4	1.0	1.0	0.56
5	1.0	0.90	0.55
6	1.0	0.95	0.56
7	1.0	1.0	0.54
8	1.0	1.0	0.55
9	1.0	0.95	0.57
10	1.0	0.90	0.54
11	1.0	0.95	0.53
12	1.0	0.90	0.56
13	1.0	1.0	0.56
14	1.0	0.97	0.55
		$\bar{A}Q_{PF}$ =0.958 $m^3.(Ø)^{-1}$	X_1 = Eave(oc) = 0.551$kW(m^3\text{-}Ø)^{-1}$
			$S_1 = \sigma_{oc}$ =0.011 $kW(m^3\text{-}Ø)^{-1}$

Here,

Q_{in} = Design capacity = $1.0m^3.(Ø)^{-1}$

= Water supply to UFM measured by AFM 1 **(**Figure 4.1**)**

Q_{out} = Water output from UFM measured by AFM 2 **(**Figure 4.1**)**

Eave(oc) = Average energy without process control devices

Q_{PF} = Average permeate flux output from UFM

σ_{wc} = Standard deviation without process control devices

Table 4.3 shows the energy consummation rate in producing permeate flux and supply to end users. Here, *Eave(oc)* is the average energy consumption rate over 14 experimental runs. *Eave(oc) is* estimated from Equation 3.14. σ_{OC} is standard deviation of energy consummation rate. The σ_{oc} is estimated from Equation 3.2. The characteristics of the average energy consummation rate over 14 experimental runs is also presented in Figure 4.6.

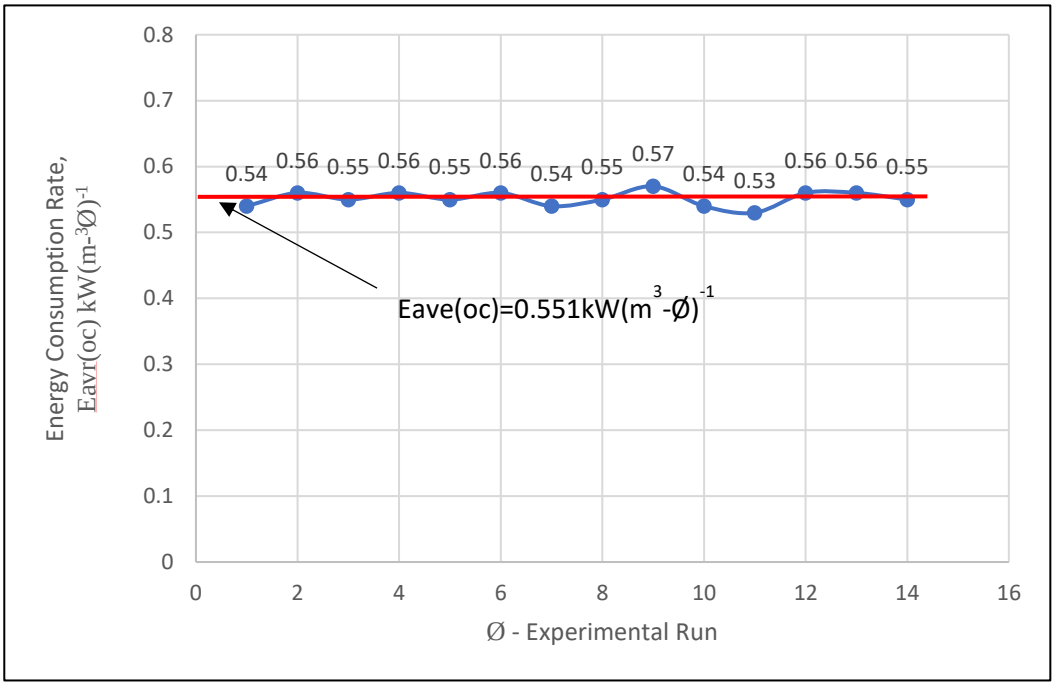


Figure 4. 4: Energy Consumption Pattern of UFM's Pump when Operate Without Process Control Devices

Figure 4.4 and Table 4.3 demonstrate the average energy consumption pattern of UFM's pump. The average energy consumption rate is 0.55kW $(m^3 - Ø)^{-1}$. The total energy consumption of the UFM is listed in Table 4.4.

Table 4. 4: Average Energy Consumption by the UFM

Equations	Data Sources	Results
Required water outputs from UFM and used. Equation 3.4 $Qt = Q_{out} x Ø$	Table 4.5 Q_{out} =0.958 $m^3(Ø)^{-1}$ Ø=14 runs	Qt =13.41 m^3
Total energy consumed by the UFM. Equation 3.18 $Etave(oc)=E_{ave}(oc)xQt(oc)$	Table 4.5 Eave=0.55kW $(m^3 - Ø)^{-1}$ Table 4.5, Column 4.0. Ø=14 runs	7.7kW
Efficiency of the UFM without process control devices. Eq. (3.7) $Ŋ(oc) = \frac{Qcons\ m^3}{Qpm^3} 100$	Table 4.5, Colum 3 Total water supply, Qp_{Ft} = 0.958x14= 13.41m^3 Water consumed by the end users Qcons =10.0 m^3	Ŋ(oc) =74.5%

The water supply required for the 14 runs is 13.41m^3 for 7 hours, and the end users consumed only 10.0 m^3 at the 7.7 kW energy consumption. The wastage of water output, Q_{PFt} (13.41-10) m^3 is 3.41 m^3 and the efficiency of water consumption without the process control devices is 74.5%.

4.9 Experiment with Process Control Devices for Measuring Energy Consumption Rate

The average energy consumption [*Eave(wc)]* from Equation 3.14. The σ_{wc} is standard deviation of energy consumption rate, which can be estimated from the equation. Equation 3.2. The feed water rate to the UFM can be estimated from Equation 4.1**.** Q_{out} (permeate) rate of UFM can be estimated from Equation 4.2. The experiment data with Process Control device at RPM 1170 is listed in Table 4.7.

Table 4. 5: Energy Data when Plant Operate with Process Control device at RPM 1170

Ø	Qin [m^3(Ø)$^{-1}$] to UFM	Qout [m^3(Ø)$^{-1}$] from UFM	Eave(wc) kW(m-^{3}Ø)$^{-1}$
1	0.78	0.4	0.42
2	0.78	0.5	0.43
3	0.78	0.6	0.43
4	0.78	0.8	0.42
5	0.78	0.9	0.42
6	0.78	1	0.43
7	0	0.9	0
8	0.78	0.8	0.42
9	0.78	0.8	0.42
10	0.78	0.8	0.43
11	0.78	0.7	0.43
12	0	0.6	0
13	0.78	0.5	0.42
14	0.78	0.4	0.43

	Average Qin = 0.72 m^3. $(Ø)^{-1}$	Average Qout = 0.69 m^3. $(Ø)^{-1}$	X_2 = Eave(wc) = 0.364 kW(m^3-Ø)$^{-1}$
			$S_2 = \sigma_{wc}$ = 0.154 kW(m^3-Ø)$^{-1}$

Table 4.5 shows that the average feed water rate to UFM is 0.72 m^3. $(Ø)^{-1}$ and the supply rate of permeate is 0.69 m^3. $(Ø)^{-1}$ at UFM plant operate for 10.0 m^3 for 7 hours at a β value 1.1, The energy consumption of UFM to produce 0.69 m^3. $(Ø)^{-1}$is 0.364 kW(m^3-Ø)$^{-1}$with a standard deviation of 0.154 (σ_{wc} = 0.154). The characteristics of the average energy consumption rate over 14 experimental runs is also presented in Figure 4.7.

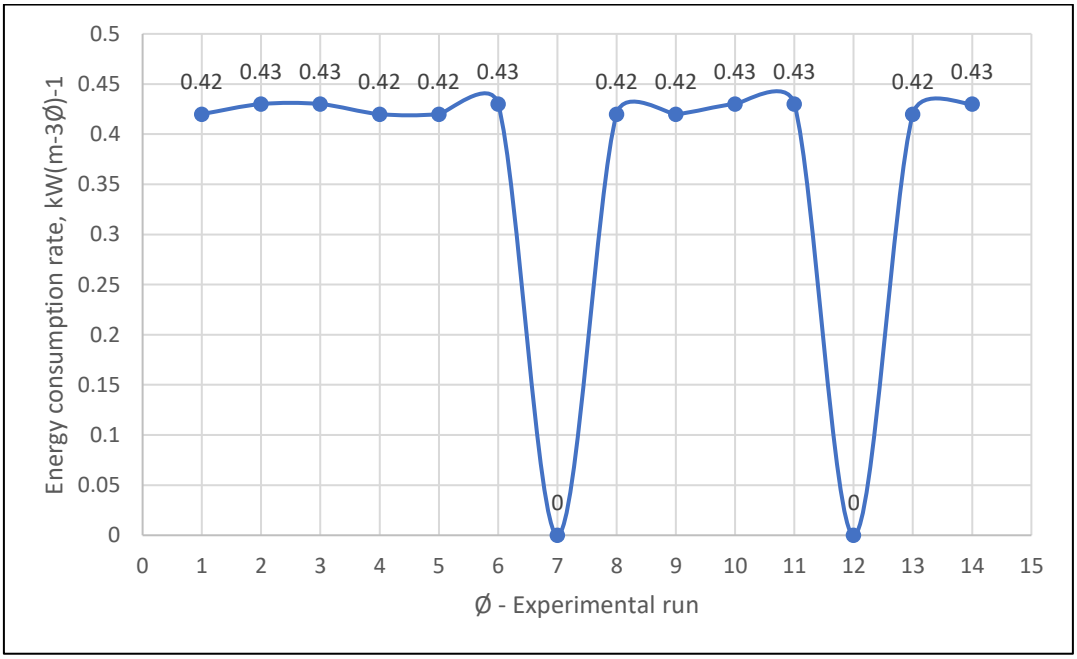


Figure 4. 5: Energy Consumption Pattern with Process Control Device

Figure 4.5 demonstrates that the total pump operating time in a cycle was 6 hours. Below are detailed explanations of characteristics of graph pattern for Figure 4.7.

i. The blue line with data points represents the energy consumption rate for each experimental run.

ii. Each data point is marked with its corresponding energy consumption rate value.

iii. Ø (1-6): Energy consumption occurred due to the pump running. This indicates that the water is consumed by consumers.

iv. At Ø=6, the high-level sensor (HLS) triggered, causing the pump to cut off. The energy level then dropped to zero.

v. At Ø=7, the energy consumption became zero. Until the water level reaches at low level, the Low-Level Sensor will trigger the pump and start to fill water in the tank

vi. At Ø (8-11), energy was consumed as the pump was activated. The water level in the tank increased until it reached the high-level, which caused the pump to trip.

vii. At Ø=11, the high-level sensor (HLS) triggered, causing the pump to cut off. The energy level then dropped to zero.

viii. At Ø=12, the energy consumption became zero. Until the water level reaches at low level, the Low-Level Sensor will trigger the pump and start to fill water in the tank.

ix. At Ø (13-14), energy was consumed as the pump was activated. The water was supplied to the tank accordingly.

Note that at Ø=6-7 and Ø=11-12, the graph shown that the level sensor has triggered the pump due to water demand. This is because the water consumption by the consumer is at peak time (rough estimate at peak hours of water demand from 11am to 2pm).

Table 4. 6: Average Energy Consumption and Efficiency of the UFM

Equations	Data Sources	Results
Required water outputs from UFM and used. Eq (3.4) $Qt = Q_{out} x Ø$	Table 4.7. Column 2.0 $Q_{out} = 0.78\ m^3(Ø)^{-1}$ Ø=12	$9.36m^3$
Total energy consumed by the UFM. Eq (3.16).	Table 4.7. Column 4. $Eave=0.364\ kW(m^3Ø)^{-1}$	3.4kW

Etave(wc)= $E_{ave(wc)}$ x $Qt_{(wc)}$	Table 4.7, Column 3. Qt=9.36m^3	
Efficiency on water output of the UFM with process control devices. Eq.(3.7) $\eta(wc) = \frac{Qcons\ m^3}{Qp\ m^3} 100$	Table 4.7, Colum 3 Qp_t =9.36 m^3 Water consumed by end users Qcons =10.0m^3	$\eta(wc)$ = 93.6%
Efficiency on energy consumption rate. Eq. (3.20) $\eta(E_{ave}) = \frac{Eave(oc)-Eave(wc)}{Eave(oc)} 100$	Chapter 3, Equation 3.20 Energy efficiency can be saved by $= \frac{(7.7-3.4)}{7.7} 100$	$\eta(E_{ave})$ = 55.8%

The average energy consumption rate was 0.364 kW (presented in Table 4.7 column 4) $(m^3\text{-Ø})^{-1}$ over the 6 pump operating hours. Equation 3.18 is estimated for determining total energy consumption during 6 hours of plant operation. Equation 3.16 is estimated to determine the required water flow [$Qt_{(wc)}$]. Table 4.6 and Figure 4.5 present the outcomes of the research conducted with process control devices. The findings demonstrate that, through the utilization of process control devices, the pump operating period was reduced by 1 hour in a set of experiments comprising 14 runs. This reduction contributes to a saving in the energy consumption rate [$kW(m^3)^{-1}$] and minimizes water wastage.

4.10 Evaluate the Impact of Process Control Devices for Measuring Energy Consumption Rate

The energy consumption rate of UFM in Permeate Flux Production performance has been utilized to assess the impact of process control devices. Referring to both Table 4.3 and Table 4.4, we observe the average energy consumption rate when WF is performed both

without and with process control devices. The influence of process control devices on UFM's energy consumption rate in Permeate Flux Production performance is evaluated through the estimation of Equation 3.15.

$$\frac{\Delta Et}{10m^3} = Eave(oc)t - Eave(wc)t \qquad \textbf{(Equation 4.6)}$$

$$= (7.7 – 3.4)\ kW(m^3)^{-1}$$

$$= 4.3\ kW(m^3)^{-1} \text{ a day for } 10\ m^3 \text{ permeate flux}$$

$$\frac{\Delta Et}{1m^3} = 0.43\ kW(m^3)^{-1} \text{ a day}$$

Here, ΔE_t is the amount of energy saved (wastage reduced) by process control devices for producing for 1 m^3 permeate flux a day or 0.43 $kW(m^3)^{-1}$. The findings presented in Equation 4.6 demonstrate that the difference of these two processes is positive and that process control devices have contributed to reduce energy consumption rate. The Equation 4.6 demonstrates that the process control devices have made a positive contribution to reduce energy consumption rate by 0.43$kW(m^3)^{-1}$. In this regard, the research question is 'whether the contribution of process control devices is significant?'

4.11 Hypothesis Test to Check Whether Process Control Devices Has a Significant Impact on The UFM Performance in Energy Consumption

In order to test the hypothesis, we employed the models outlined in Section 3.5. This testing phase utilized a paired-samples t-test with a 95% significance level, specifically applied to the energy consumption rate. The energy consumption rate (S_p) was estimated from Equation 3.10, utilizing data from both Table 4.3 and Table 4.5. The Detail estimate is attached in appendix L.

The estimated value of S_p is: 0.109

Here, from Table 4.3

S_1=standard deviation of sample means 1= 0.011 $kW(m^3\text{-}Ø)^{-1}$

X_1-average of sample mean 1 = *Eave(*oc) = 0.55 kW$(m^3\text{-}Ø)^{-1}$

N_1 is sample size = 14.

From Table 4.5,

S_2=standard deviation of sample means 2 = 0.154 $kW(m^3\text{-}Ø)^{-1}$

X_2-average of sample mean 2 = *Eave(*wc) = 0.364 $kW(m^3\text{-}Ø)^{-1}$

N_2 is sample size = 14.

The degree of freedom can estimate Eq. (3.11).

df= (N_1+ N_2–2) = 26.

The 't_{st}' is estimate from Equation 3.9.

The estimated value of t_{st} is = ± 4.45 (Detail estimate is attached in appendix M).

Based on the paired-samples t-test and t table, with df at 26 and 95% confidence level, the 'critical value t=2.056 (t table is attached in appendix N). This value is lower than 4.45, and the corresponding P-value is less than 0.05. The statistical data supporting these findings is presented in Figure 4.8.

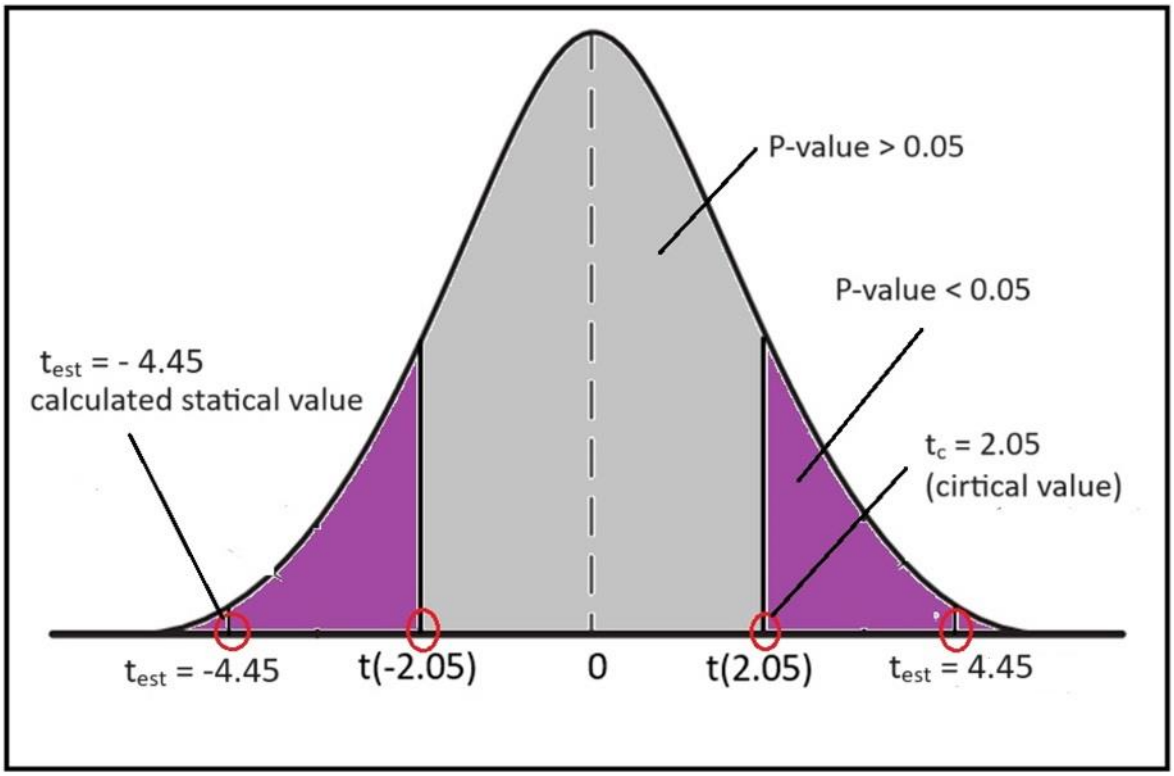


Figure 4. 6: 't' score for Hypothesis test with mean value of Energy consumption rate

Figure 4.6 demonstrates that the estimated 't_{est}' value is less than the critical value (t_c), P-value of 't_{est}' is less than 0.05 (P-value <0.05). Based on the obtained findings, the study provides sufficient information to assert that the means of the two sets of data are not equal, leading to the rejection of the null hypothesis (H_o). Simultaneously, the alternative hypothesis (H_a) is accepted. This signifies that process control devices have played a substantial role in decreasing the energy consumption rate of UFM during the production of permeate flux. This discovery leads to the conclusion that the impact of process control devices on reducing the energy consumption rate of UFM in producing permeate flux is indeed significant. Consequently, the integration of process control devices is deemed necessary in the WF process.

4.12 Findings and Answer to the Research Question Two

The results of the data analysis from experiments related to Objective One are presented in Table 4.3, Table 4.5, Figure 4.5, and Figure 4.6. These findings demonstrate that process control devices contribute to the saving of the energy consumption rate of UFM in permeate flux yield. The experimental data, both with and without process control devices, were analysed and subjected to the 'paired test' at a 95% confidence level. The findings demonstrate that process control devices have significantly contributed to reducing the energy consumption rate by 0.43 $kW(m^3)^{-1}$ in the production of permeate flux. This contribution is deemed significant at P-value < 0.05. The finding is relevant to objective two, lead to the conclusion that research objective one has been achieved, thereby addressing research question two.

4.13 Research Finding on Relating to the Objective Three

The experiment was conducted using UFM (MP4040/0.001) in accordance with objective three as outlined in Chapter 1, Section 1.4.iii. It was set up to assess the optimization of process parameters for achieving optimal performance from the UF membrane. The methodology, data collection methods, and data quality improvement are detailed in Chapter 3.0, Section 3.11. A total of fourteen (14) experimental runs for objective three are listed in Table 4.3. The equipment setup, as presented in Figure 3.2 was employed to conduct the experiments for objective three. This experiment will answer the question "What is the empirical model that could be used to predict optimum level of permeate flux [$m^3(sqm)^{-1}$] with respect to feed pressure (bar) and energy consumption rate [$kW(m^3)^{-1}$] at the effect of process control devices?".

4.14 The Conceptual Input-Outputs Model of UFM in Producing Permeate Flux

Energy and feed pressure are the potential inputs for producing product water (permeated flux) by UFM. The conceptual model for input-output of UFM in producing permeate flux is presented in Figure 4.7, which relates to the model present in Equation 3.22 and Equation 3.23:

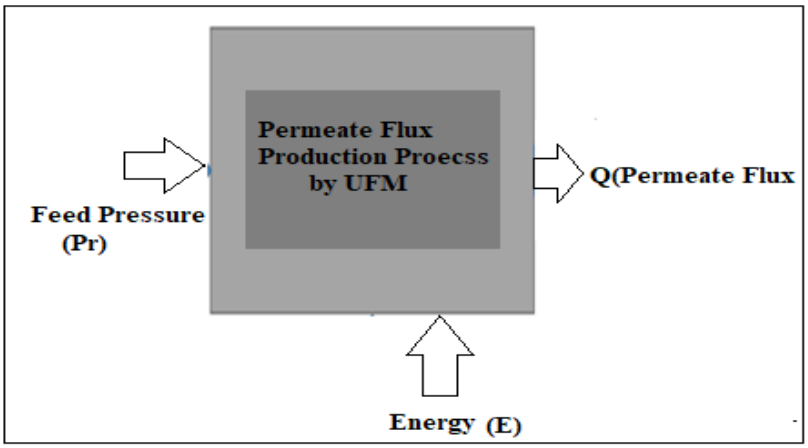


Figure 4. 7: Input-Out Model of UFM in producing permeate flux

In the context of this system, Feed pressure (bar) serves the purpose of overcoming the resistance of the UFM to achieve the optimal level of permeate flux. Energy (E) is defined as the energy consumption rate [kW(m3)$^{-1}$] of the UFM in achieving the optimum permeate flux. Both the permeate flux and energy consumption rate are interdependent on the feed pressure. The performance of the UFM can be accurately represented by the following model:

$$\text{Performance} = \int (Q, Pr, E) \qquad \textbf{(Equation 4.7)}$$

Figure 4.9 and Equation 4.7 show that the permeate production process is a non-linear process which can be expressed mathematically by Equation 4.8.

$$Q_{permeate\ flux} = A_O (Pr)^{\alpha} . E^{\beta} K \qquad \textbf{(Equation 4.8)}$$

The linear form of this equation is presented by Equation 4.9.

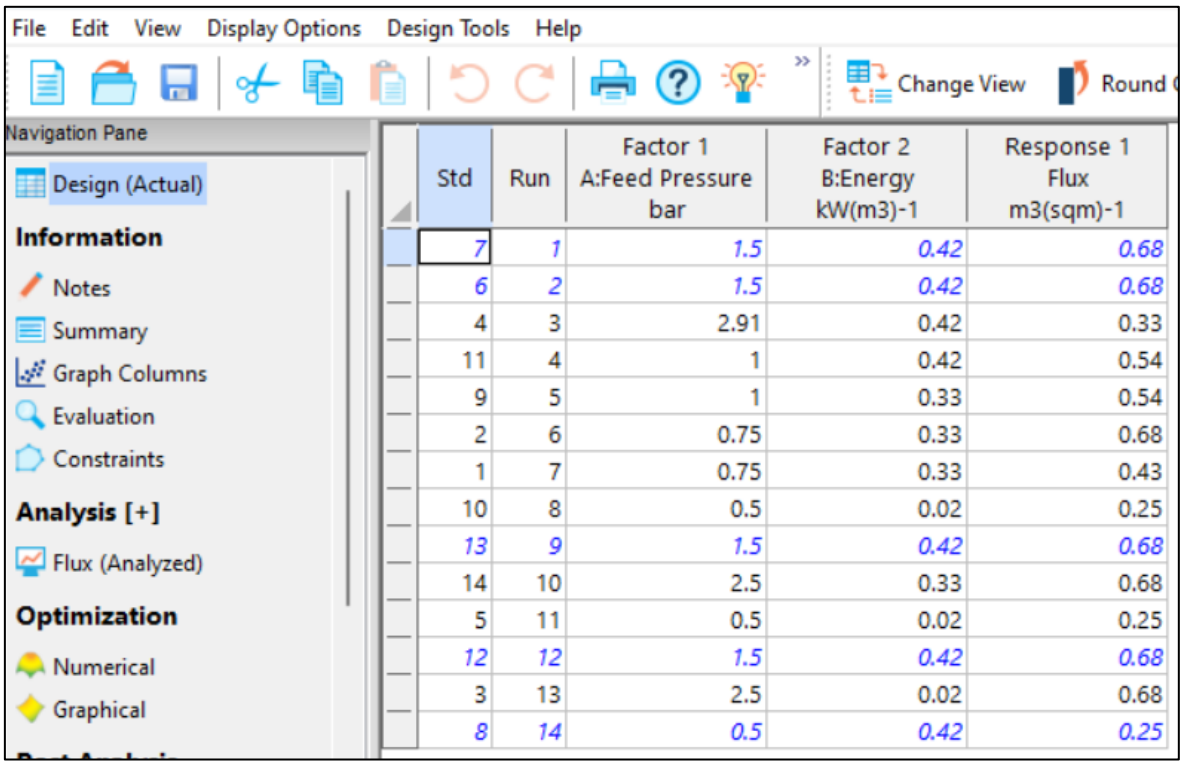
$$\log(Q_{permeate\ flux}) = \log A_O + \alpha \log(Pr) + \beta \log(E) + \log K \qquad \textbf{(Equation 4.9)}$$

The intercept of the line at the y-axis, denoted as $A_{O,}$ represents a crucial point in this analysis. The coefficient of Pr is 'α' which contributes to Q_{PF} ($Q_{permeate\ flux}$) yield. Simultaneously, the coefficient 'β' corresponds to the variable E, which contributes to Q_{PF} yield. Additionally, in the regression term model, the error term is ε and K is constant.

4.15 Data Analysis and Model Development for Performance Optimization

Experimental data relating to the energy consumption, permeate flux and feed pressure were recorded in Table 4.9. The Table 4.9 is developed in accordance to Table 3.7 and attached in Appendix 4.1: Data for Center Point and Surface Response.

Table 4. 7: Experimental Data of Independent and Dependent Variables for Process Optimization



Std	Run	Factor 1 A:Feed Pressure bar	Factor 2 B:Energy kW(m3)-1	Response 1 Flux m3(sqm)-1
7	1	1.5	0.42	0.68
6	2	1.5	0.42	0.68
4	3	2.91	0.42	0.33
11	4	1	0.42	0.54
9	5	1	0.33	0.54
2	6	0.75	0.33	0.68
1	7	0.75	0.33	0.43
10	8	0.5	0.02	0.25
13	9	1.5	0.42	0.68
14	10	2.5	0.33	0.68
5	11	0.5	0.02	0.25
12	12	1.5	0.42	0.68
3	13	2.5	0.02	0.68
8	14	0.5	0.42	0.25

Table 4.7 demonstrates the relationship among the feedwater pressure (Fp), flux(Q), and energy consumption (E). The optimum value of Pr, Q_{PF}, and 'E' are 1.5 bar, 0.68 $m^3(sqm)^{-1}$ and 0.42 [$kW(m^3)^{-1}$]. The data is presented in Figure 4.10 and Figure 4.11 and attached in appendix 4.2 tabulated data for DOE.

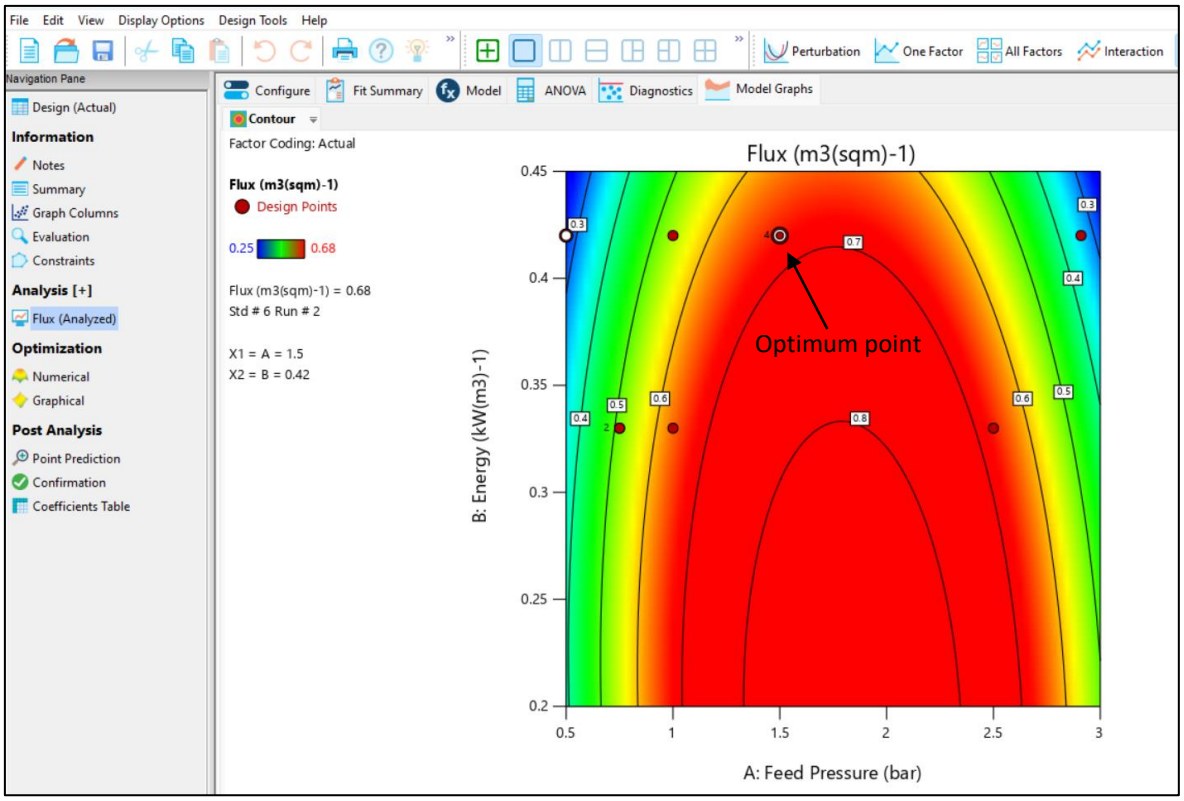


Figure 4. 8: Relationship between Feed Pressure, Flux and Energy Consumption

The relationship between Feed Pressure, Flux, and Energy Consumption is illustrated by the contour in Figure 4.8. The red contour zone signifies the highest energy consumption within the system, attributed to the water demand (flux) imposed by the consumer. This observation indicates that the system expends the most energy under these conditions. On the other hand, the green contour zone denotes a lower level of energy consumption, suggesting that the pump is in its initial stage, either starting or stopping. This behaviour is triggered by the level sensors. In this phase, the energy usage remains relatively low. Lastly, the blue contour zone represents nearly zero energy consumption. This indicates a state where the energy levels are minimal, highlighting specific operational conditions where the system requires negligible power.

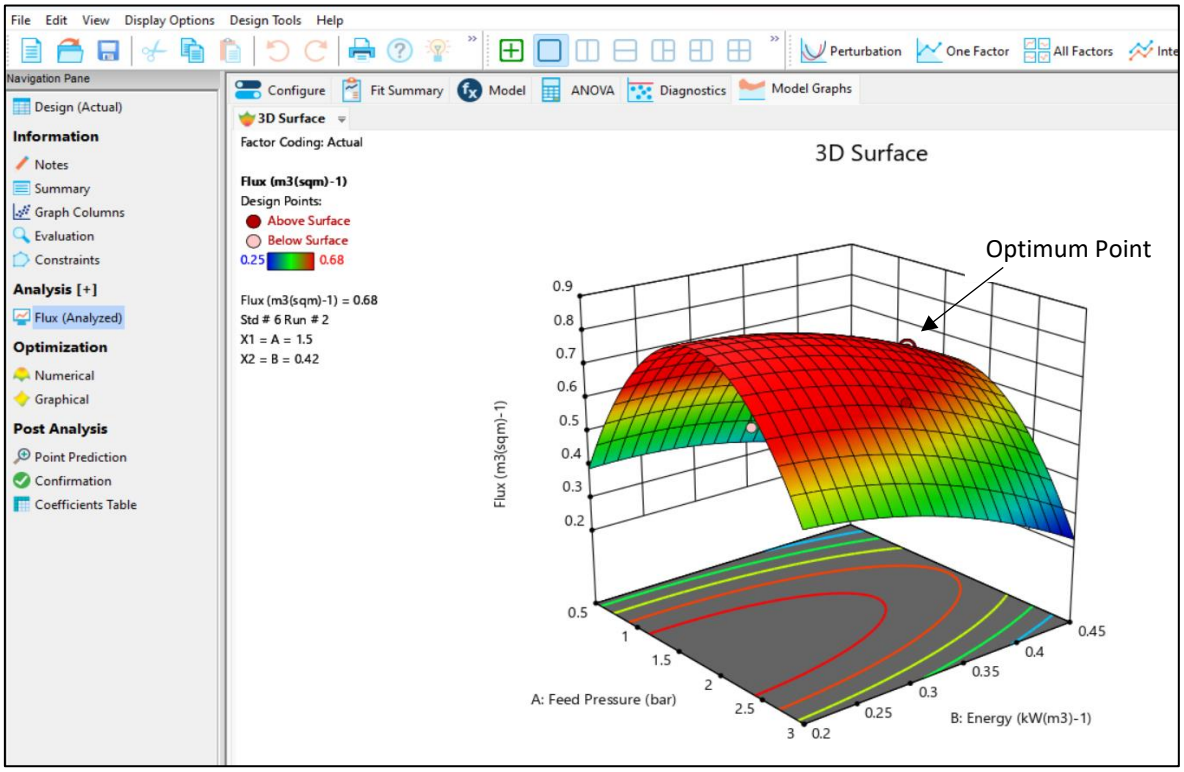


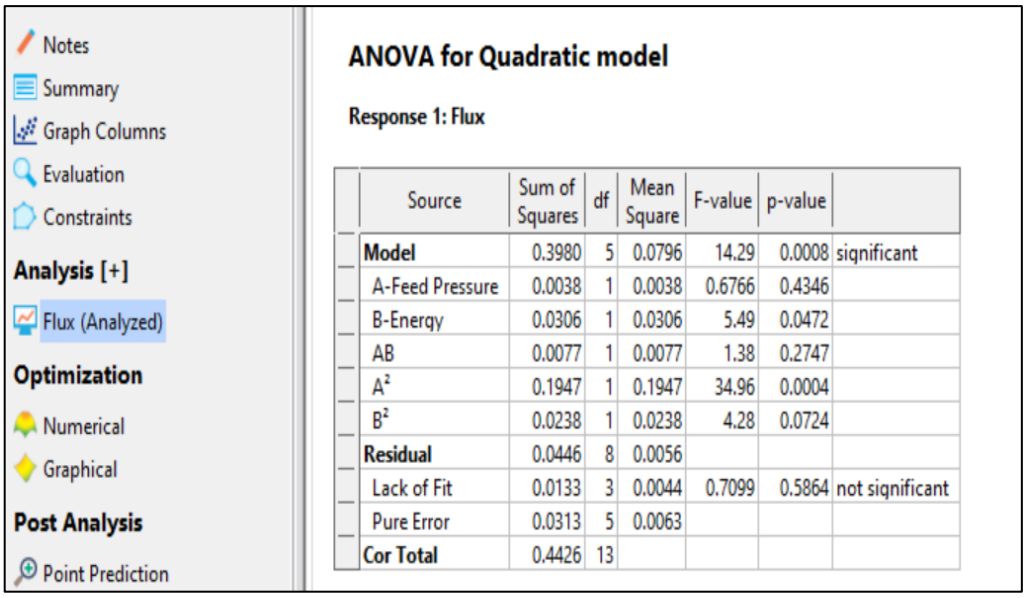
Figure 4. 9: The 3D plots of Surface Respond Diagram between Feed Pressure, Energy Consumption and Flux

The 3D plots of surface respond diagram in Figure 4.9 presents the optimum performance of the UFM on productivity in permeate flux. The optimum points are feed pressure is 1.5 bar, energy consumption rate is 0.42 kW$(m^3)^{-1}$ and permeate flux is 0.68 [$m^3(sqm)^{-1}$]. The 3D plots of the surface response diagram also illustrate that when the water level reaches a low point, the pump starts at a low pressure, minimizing energy usage. As water demand increases, the energy consumption also rises proportionally, leading to an increase in permeate flux. When a high-water level is detected, the level sensor sends a signal to stop the pump.

4.16 Model Analysis and Experimental Findings

The DoE output and ANOVA are listed in Table 4.8. The results of the experiment were analysed, and its output is presented in the 3D contour model as demonstrated in Figure 4.10 and Figure 4.11. This is attached in Appendix 4.3(a): Data for Significance Study on Operational Impact and Appendix 4.3(b): Operational Coefficients Table.

Table 4. 8: ANOVA Analysis



ANOVA for Quadratic model

Response 1: Flux

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.3980	5	0.0796	14.29	0.0008	significant
A-Feed Pressure	0.0038	1	0.0038	0.6766	0.4346	
B-Energy	0.0306	1	0.0306	5.49	0.0472	
AB	0.0077	1	0.0077	1.38	0.2747	
A^2	0.1947	1	0.1947	34.96	0.0004	
B^2	0.0238	1	0.0238	4.28	0.0724	
Residual	0.0446	8	0.0056			
Lack of Fit	0.0133	3	0.0044	0.7099	0.5864	not significant
Pure Error	0.0313	5	0.0063			
Cor Total	0.4426	13				

Table 4.8 shows that the intercept of regulation line $A_O = 0.8071$. The P-value of feed water pressure $\alpha = 0.4346$, The P-value of energy consumption $\beta = 0.0472$. The stand standard error of regression (ε) = 0.0528. The desired statistical model could be rewritten as linear form shown in Equation 4.10.

$$\log(Q_{pF}) = \log 0.8071 + 0.4346 \log Pr + 0.0472 \log E + \log 0.0528 \quad \textbf{(Equation 4.10)}$$

Note: The standard deviation error in estimation of **Equation 4.10** for $\log 0.0528$ is very small, and therefore the standard deviation error is to be omitted. The non-linear form of that model could be presented by Equation 4.11.

$$Q_{PF} = 0.8071.(Pr)^{0.4346}.\ E^{0.0472} \quad \textbf{(Equation 4.11)}$$

Equation 4.11 is the nonlinear form of the developed model. Table 4.9 describes fit statistics of the data.

Table 4. 9: Fit Statistic

Fit Statistics | Model Comparison Statistics

Fit Statistics

Std. Dev.	0.0746		**R^2**	0.8993
Mean	0.5250		**Adjusted R^2**	0.8364
C.V. %	14.22		**Predicted R^2**	0.7803
			Adeq Precision	8.7843

Table 4.9 shows the R^2 value which has a relationship with the regulation. A value of R^2 89.93% indicates that the dependent variable is responding to the independent variable at the degree of 89.93%. Any value of R^2 more than 0.5 (R^2) is accepted for a good fit of regression. However, the value R^2 is 89.93 means, the put (dependent variable) is 89.93% associated with inputs, which is an indication of good fit of data in the regression.

4.17 Model Analysis

The shaded area in this Figure 4.10 represents the contribution of Pf to Q_{PF}, which is more than 95% (p>0.05). This finding affirms that the contribution of Pf to Q_{PF} is not significant at 95% confidence level. Nevertheless, the impact of feed pressure on permeate flux may not be entirely negligible, as it does contribute to enhancing overall energy efficiency and performance.

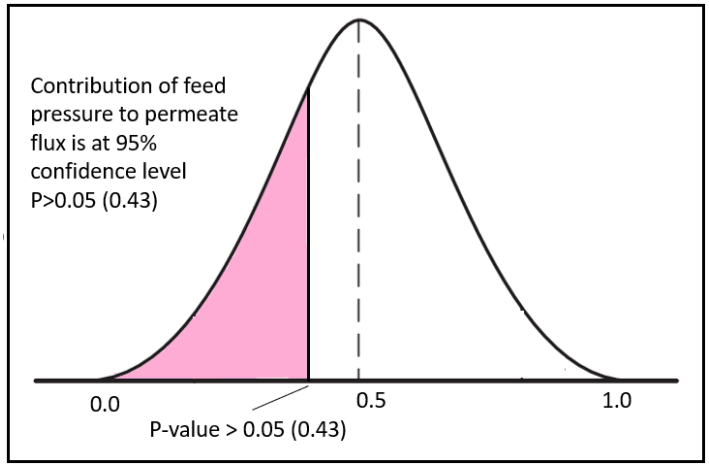


Figure 4. 10: Contribution of feed pressure to Permeate Flux

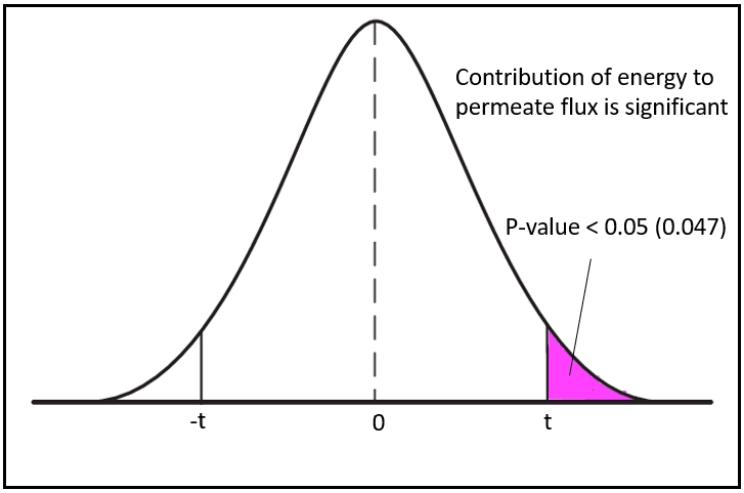


Figure 4. 11: Contribution of Energy to Permeate Flux

The shaded area in this Figure 4.11 represents the contribution of Energy to Q_{PF}, which is more than 95% ($p<0.05$). This finding affirms that the contribution of Energy to Q_{PF} was significant at 95% confidence level.

4.18 Model Validation With 14 Experimental Outputs

The graph in Figure 4.12 presents the "x-axis" as the actual experimental outputs (actual data response) of 14 runs; and "y-axis" as the model estimate in Equation 4.11. It can be deduced from Figure 4.12 and Appendix 4.5 (a): External Studentized Residuals and Appendix 4.5 (b): Internal Studentized Residuals, that the optimal Q_{PF} output of 14 runs is 0.68 $m^3(sqm)^{-1}$, whereas the value of model prediction (fitted value on the regression line) is 0.679 $m^3(sqm)^{-1}$, This finding demonstrates that average error in the prediction model with 14 runs is about 5.28%.

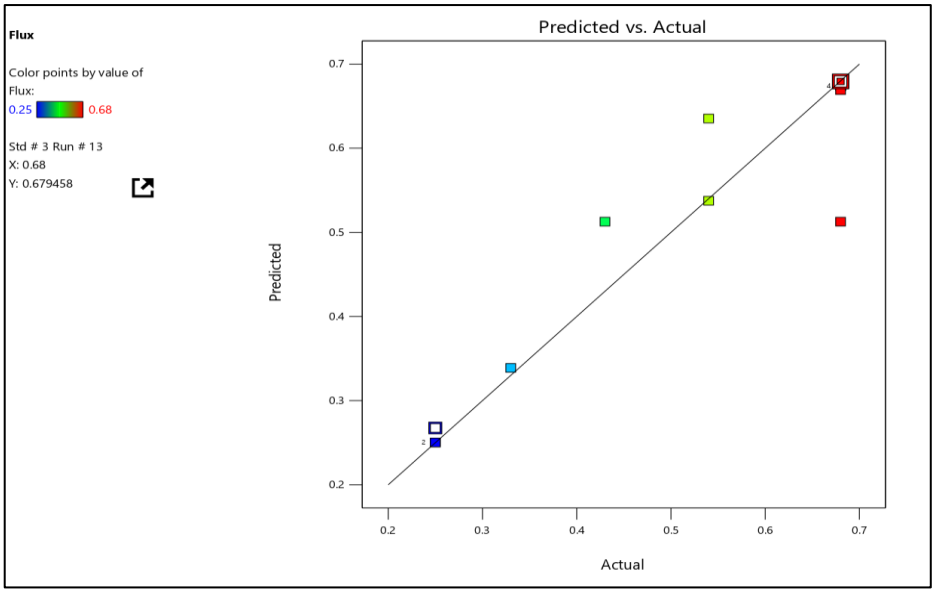


Figure 4. 12: Distribution of Predicted and Actual Outputs for Model Estimation

4.19 Comparison Data Based on RSM Model and Experimental Data

Table 4.8 provides a comparison between the data derived from the Response Surface Methodology (RSM) model and the experimental data. The experimental and RSM data exhibit close similarities, with values of 0.66 $m^3(sqm)^{-1}$ and 0.68 $m^3(sqm)^{-1}$respectively. This study concludes that the optimal values for feed pressure, permeate flux, and energy consumption rate can be determined through the regression model presented in Equation 4.11 as well as through on-site experimental data. As a result, the research successfully achieves objective number three, providing a comprehensive answer to research question three.

Table 4. 10: Comparison Data Based on RSM Model and Experimental Data

Parameters	Based on RSM Model (DOE)	Based on Experimental Data	Deviation (%)
Input			
Feed Pressure	1.5 bar	1.5 bar	ΔPbar = 0 (%)
Energy	0.426 $kW(m^3)^{-1}$	0.425 $kW(m^3)^{-1}$	ΔkW= 0.23%
Output			
Permeate Flux (Q)	0.68 $m^3(sqm)^{-1}$	0.66 $m^3(sqm)^{-1}$	ΔQ = 2.94%

Note: Base on RSM Model (DOE) result can be referred to figure 4.9.

Table 4.10 demonstrates that the deviation between the experimental findings and findings from RSM simulation conducted by RSM is very close and within 3%, which is within acceptable limit.

4.20 Research Findings and Answer to the Question Three

The experimental data has been used to develop model, which is presented in Equation 4.11.

$$Q_{PF} = 0.8071\ (Pr)^{0.4346}.\ E^{0.0472}$$

The optimum value of feed water pressure estimated by software by using experimental is 1.5 bar (Figure 4.9) at P-value > 0.05 (0.4346, Table 4.8). The optimum value of energy consumption estimated by software by using experimental is 0.426 (Figure 4.10) at P-value < 0.05 (0.0472, Table 4.8).

The experimental data analysis presented here revealed the optimum value of the research variables related to the research question no 3.0 and objectives 3.0. Thus, this research findings are answered the question no 3.0.

4.21 Conclusion and Chapter Summary

In addressing objective one, the detailed findings are presented in Section 4.2.5. The results of the data analysis, depicted in Table 4.1, Table 4.2, Figure 4.1, and Figure 4.2, indicate a pivotal role of process control devices in adjusting feed pressure and influencing UFM performance in permeate flux yield. Two experiments were conducted to assess the impact of these devices on permeate flux, and the data were analysed using the 'paired test' at a 95% confidence level. The findings reveal a significant contribution of process control devices, resulting in a savings of 3.16 m^3 of productivity per day or 31.6% (P-value < 0.05). This addresses the research question and ultimately concludes the achievement of objective one.

For objective two, the results demonstrate that process control devices effectively reduce the energy consumption rate of UFM, leading to an improvement in permeate flux yield. The analysis of experimental data, both with and without these devices, using a 'paired test' at a 95% confidence level, reveals a statistically significant saving the energy

consumption rate by 0.43 $kW(m^3)^{-1}$ or 55.8% (P-value < 0.05). Thus, this addresses the research question and ultimately concludes the achievement of objective two.

The attainment of objective three is evident through the outcomes presented in Table 4.13, which demonstrate that both model development and site experimental data have reached their optimum values. The study draws a conclusive inference that the regression model represented by Equation 4.11 effectively determines the optimal values for feed pressure, permeate flux, and energy consumption rate. As a result, Objective Three has been successfully achieved, providing a comprehensive answer to research question three. In summary, the research objectives have been accomplished with success.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Chapter Overview

This chapter presents the conclusion and recommendations derived from the study. Section 5.2 outlines the research outcomes, while Section 5.3 explores the novelty of the research and its contribution to the knowledge system. The implications of the research outcomes are discussed in Section 5.4, and Section 5.5 addresses the limitations of the study. Section 5.6 provides a summary of the study. Finally, Chapter 5 concludes with recommendations for future optimization of ultrafiltration (UF) for various water sources.

5.2 Outcome of Research

Experiments were conducted to achieve the research goals, specifically focusing on optimizing the performance of UFM. Three sets of experiments were undertaken to determine the optimum performance. The fundamental elements of this study included process control devices, output optimization, and the application of green technology aimed at producing clean water to protect public health, aligning with Sustainable Development Goals 6 (SDG6) and 12 (SDG12). The research outcomes have potential benefits for the industry, society, environment, and economy. These outcomes are illustrated in Figure 5.1.

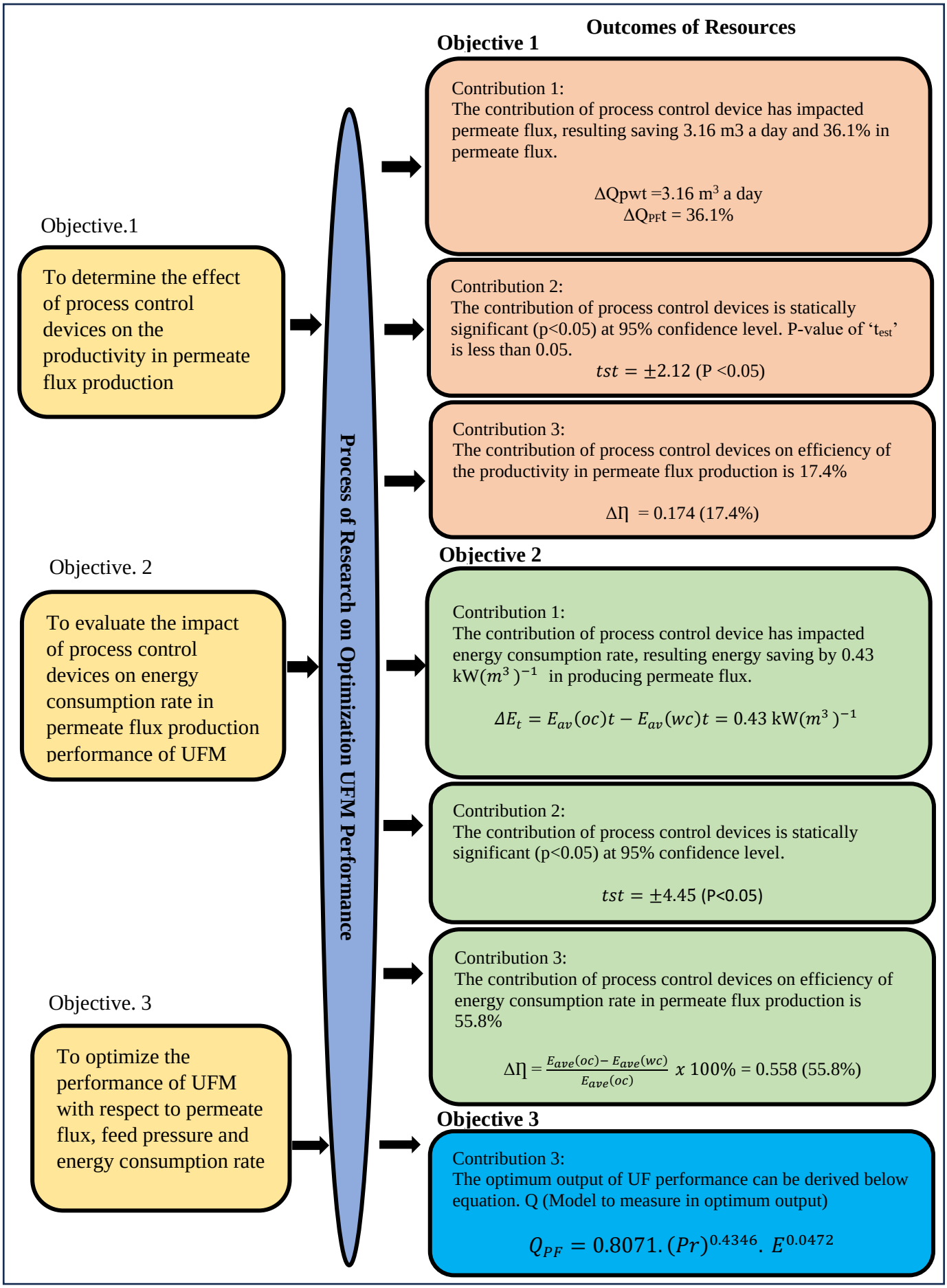


Figure 5. 1: Outcomes of Research - Modelling of CU of UFM Plant

5.2.1 Research Outcome Number One

The research outcome as stated in Figure 5.1 for the objective one:

i. The contribution of process control device has impacted permeate flux, resulting a saving 31.6% of permeate flux.

ii. The contribution of process control device is statistically significant ($p<0.05$) at 95% confidence level

iii. The contribution of process control device on efficiency of the productivity in permeate flux production is 17.4%

5.2.2 Research Outcome Number Two

The research outcome as stated in Figure 5.1 for the objective two:

i. The contribution of process control device has impacted energy consumption rate, resulting energy saving by $0.43\text{kW}(\text{m}^3)^{-1}$ in producing permeate flux.

ii. The contribution of process control device is statistically significant ($p<0.05$) at 95% confidence level

iii. The contribution of process control device on efficiency of energy consumption rate in permeate flux production is 55.8%

5.2.3 Research Outcome Number Three

Objective three of the research was analyzed, and the resulting outcomes were found to be interconnected with both objective one and objective two. The relationship between feed pressure, flux, and energy consumption can be illustrated as independent and dependent variables. These parameters are mutually related and can be utilized to determine the

achievement of objective three. A 3D plot Respond Surface Diagram as presented in Figure 4.3(b) of Chapter 4 was developed using Design Expert software, version 13. From the outcome result in Figure 5.1, the optimum output of UF performance can be derived in mathematical equation below:

$$Q_{PF} = 0.8071.(Pr)^{0.4346}.\ E^{0.0472}0.528$$

The comparison data derived from both modelling and experimental sources exhibit consistency. The results obtained through Response Surface Methodology (RSM) modelling have been substantiated by corresponding experimental data, as indicated in Table 4.13. Consequently, it can be inferred that the research objective three has been successfully accomplished, and the query posed in research question three has been addressed.

5.3 Implication of Research Outcomes

Optimizing the performance of ultrafiltration (UF) membranes and integrating them with process control devices can significantly enhance various industrial and water treatment applications. UF membranes are widely used to separate suspended solids, microorganisms, and macromolecules from liquids. When these membranes operate efficiently, they typically require lower pressures and energy input for filtration, leading to reduced energy consumption, lower greenhouse gas emissions, and a smaller carbon footprint. Optimized UF systems, aided by process control devices, can further enhance energy efficiency by regulating pumps, valves, and other components to align with filtration needs, resulting in cost savings and environmental benefits.

Improved productivity in permeate flux is another key benefit. UF membranes with optimized performance achieve higher filtration efficiencies, removing a wider range of particles and contaminants from the feed solution, thus contributing to better product quality. Process control devices maintain optimal operating conditions, ensuring consistent filtration performance over time. This leads to improved product quality by ensuring a more consistent final product.

Additionally, properly controlled UF systems can extend the lifespan of membranes by preventing excessive fouling and damage caused by suboptimal operating conditions. Continuous monitoring and timely initiation of cleaning or maintenance procedures by process control devices ensure that membranes remain in good condition, reducing the frequency and cost of replacements.

Consistency and reliability are also enhanced by integrating UF membranes with process control devices. This integration ensures a more reliable and consistent filtration process, reducing the chances of unexpected downtime or fluctuations in product quality. Real-time monitoring and control enable operators to respond promptly to any deviations from desired performance, maintaining the stability of the filtration process.

In summary, optimizing UF membrane performance and integrating them with process control devices create filtration processes that are not only more efficient but also more reliable and cost-effective. These advancements hold significant potential for various industries, including water treatment, pharmaceuticals, and food and beverage, where high-quality filtration is crucial for ensuring product quality, regulatory compliance, and

sustainability goals. The impact of such innovations in these sectors is particularly noteworthy, driving improvements in both operational efficiency and environmental sustainability

5.3.1 Implication of Research Outcome to The Environment

Optimizing the performance of ultrafiltration (UF) membranes and integrating them with process control devices can significantly benefit the environment. Efficient UF membranes produce cleaner filtrate, minimizing wastewater generation and conserving water resources, which is vital in water treatment processes. Optimized UF systems consistently remove contaminants, leading to cleaner water discharge that protects aquatic environments and their species. Process control devices ensure peak efficiency, promoting sustainable resource use and reducing waste. In water-scarce regions, this optimization is crucial for efficiently treating and reusing water, enhancing conservation and sustainability. Additionally, proper process control helps quickly identify and address issues like membrane fouling or system malfunctions, mitigating environmental risks. In summary, optimizing UF membrane performance and integrating process control devices reduce wastewater generation and environmental contamination, contributing to more sustainable and environmentally responsible industrial processes.

5.3.2 Implication of Research Outcome to The Economy

The research outcomes related to optimizing the performance of UF membranes and integrating them with process control devices have significant economic implications. Improved UF systems can lead to cost savings by reducing operational expenses, energy

consumption, and maintenance costs, thereby enhancing profitability for businesses and industries. Enhanced UF membrane performance and process control contribute to higher production efficiency, resulting in increased output and potentially higher revenue. These optimizations also drive sustainability initiatives, attracting environmentally conscious consumers and investors, and enhancing a company's reputation and market appeal. Moreover, compliance with environmental and quality regulations through these optimizations reduces the risk of fines and penalties, safeguarding financial stability and reputation. High-quality products produced through optimized UF systems can also open up export opportunities, contributing to national economic growth. In summary, optimizing UF membrane performance and integrating process control devices yield economic benefits by reducing costs, increasing productivity, enhancing competitiveness, and promoting sustainable practices, which collectively contribute to economic growth and stability.

5.3.3 Implication of Research Outcome to The Industry

The implications of research outcomes related to optimizing UF membrane performance with process control devices for the industry are substantial. Enhanced UF membrane systems improve the efficiency of filtration processes, thereby reducing production time and costs. This leads to higher product quality through consistent and reliable filtration, which reduces defects and customer complaints. Additionally, energy savings and reduced maintenance contribute to lower operational expenses, increasing profitability. Companies with optimized UF systems can offer superior products or services at competitive prices, enhancing their market position. These optimized systems also align with sustainability goals, attracting environmentally conscious consumers and investors. Meeting industry standards and regulations ensures a company's legality and bolsters its

reputation. Efficient systems minimize unexpected disruptions, reducing the risk of production downtime. In summary, research outcomes in UF membrane optimization with process control devices benefit industries by boosting efficiency, product quality, cost-effectiveness, and competitiveness while promoting sustainability and regulatory compliance.

5.3.4 Implication of Research Outcome to The Society

The implications of research outcomes related to optimizing UF membrane performance with process control devices for society are far-reaching. Improved UF systems contribute to cleaner drinking water and reduce pollution in natural water sources, significantly benefiting public health. More efficient systems can lead to cost savings in water treatment, potentially lowering water bills for consumers. Additionally, optimized systems minimize the environmental impact of industrial processes, preserving ecosystems and wildlife. Better filtration ensures the production of safer and higher-quality food, beverages, and pharmaceuticals. The research and implementation of advanced systems can create job opportunities in engineering, manufacturing, and maintenance sectors. Adoption of sustainable technologies supports environmentally friendly practices, aligning with society's growing concern for the environment. Furthermore, improved systems provide a consistent and reliable supply of essential products like clean water and pharmaceuticals, enhancing public well-being. In summary, research outcomes related to UF membrane optimization with process control devices benefit society by providing cleaner water, reducing costs, protecting the environment, improving product safety, creating jobs, and supporting sustainable practices.

5.3.5 Implication of Research Outcome to The Policy Issue

The implications of research outcomes related to optimizing UF membrane performance with process control devices for political issues are multifaceted. Politically, these advancements can help industries adhere to environmental regulations, reducing potential conflicts and public concerns about pollution and water quality. Efficient UF systems also contribute to responsible resource management, aligning with political priorities on sustainability and resource allocation. The adoption of advanced technologies can stimulate economic growth, a key political objective in many regions. If the technology enhances export opportunities, it can positively impact trade relations and political diplomacy. Moreover, by addressing public concerns about environmental issues and product safety, optimized UF systems can improve public perception and trust in political leadership. In summary, research outcomes related to UF membrane optimization and process control devices can influence political issues by supporting regulatory compliance, responsible resource management, economic growth, international relations, and public confidence in addressing environmental and safety concerns.

5.4 Novelty of The Research and Contribution to Knowledge System

The implications of research outcomes related to optimizing UF membrane performance with process control devices for the knowledge system include:

i. Advancing Scientific Knowledge: Research outcomes contribute to a deeper understanding of membrane filtration technology and its integration with process control systems, enriching the knowledge base in these fields.

ii. Knowledge Dissemination: New findings are shared through academic publications, conferences, and educational institutions, fostering the spread of knowledge and expertise.

iii. Educational Opportunities: The research can lead to the development of educational programs and training resources, equipping professionals with the knowledge and skills to work with advanced UF membrane systems.

iv. Innovation and Research Funding: Successful research outcomes may attract further investment and funding for future studies and innovations in membrane technology.

v. Collaborative Efforts: Research often involves collaborations between academia and industry, strengthening the ties between knowledge institutions and practical applications.

In summary, research outcomes related to UF membrane optimization and process control devices contribute to the growth of knowledge, support educational initiatives, and drive innovation in these fields.

5.4.1 Limitation of Study

To address the limitations encountered in the current study and enhance its overall quality, several recommendations are proposed for consideration in future research. The following suggestions are presented to guide and contribute to the improvement of subsequent studies:

i. The level sensor can be substituted with instruments like a level transmitter. The signal transmitted to the pump through the controller is analogue. This analogue signal enables continuous monitoring of the water level. Moreover, the configuration options

include, but are not limited to, setpoints, high and low levels, medium processing, and alarm settings.

ii. In addition to the pressure gauge, it is advisable to incorporate additional instruments such as a pressure transmitter into the system. It is crucial to select an instrument that aligns with the specific parameters of the engineering process. This consideration is not only essential for optimizing efficiency and capacity utilization but also plays a vital role in monitoring and maintenance for cross-referencing purposes. By doing so, it ensures the authenticity of data, such as pressure readings, and minimizes the risk of errors.

iii. The plant's design can be enhanced through better engineering practices. To fully optimize the system, it is recommended to implement process control, ensuring that operations are automated. In addition to instrumentation and control measures, the integration of control valves into the process control is suggested. This enhancement aims to achieve improved capacity utilization and greater efficiency in the overall process engineering or system.

iv. By incorporating a pressure switch and pressure transmitter, the process can be checked and monitored as well as allowing cross-reference with the analogue pressure gauge. When there is a different in reading between pressure gauge and the transmitter, technician or the operator can observe it through the Distributed Control System (DCS) or Human Machine Interface (HMI). Subsequently, troubleshooting becomes necessary to solve the differential pressure and get the genuine pressure reading.

v. The installation of instruments, such as the suspended solids meter, is essential within the system. These instruments generate output results through controllers or process controls, enhancing efficiency and ensuring the accuracy of genuine data. Instant on-

site data results prove to be more accurate compared to transporting the data to the UNIMAS Lab. This approach minimizes the risk of data output results being affected or contaminated.

vi. Certainly, achieving high efficiency in both instrument and control, as well as process control, comes at a cost. Process engineering, particularly instrumentation and control, is known for its high expenses. However, despite the substantial investment required, establishing an optimal system capable of utilizing the full capacity in terms of process engineering is justified. This is due to the significant return on investment (ROI) that such an investment can yield.

5.5 Conclusion and Recommendations of the Study

In conclusion, the research outcomes have provided valuable insights into the impact of process control devices on permeate flux production and energy consumption in a UF system. The first objective revealed a significant contribution, with a 31.6% saving in permeate flux attributed to the implementation of process control devices. The second objective demonstrated a $0.43\text{kW}(\text{m}^3)^{-1}$ saving in energy consumption rate, constituting a 55.8% improvement. These findings were statistically significant at a 95% confidence level.

Moreover, the interrelation between feed pressure, flux, and energy consumption, explored in the third objective, was successfully analyzed. A 3D plot Respond Surface Diagram and a mathematical equation $Q_{PF} = 0.8071.(Pr)^{0.4346}.\ E^{0.0472}0.528$ were developed to optimize UF performance. The congruence between modeling and experimental data affirmed the validity of these results.

In summary, the research outcomes collectively underscore the positive impact of process control devices on both permeate flux production and energy efficiency in UF

systems. The achieved results not only contribute to the scientific understanding of these processes but also offer practical insights for enhancing productivity and sustainability in relevant industrial applications. The successful attainment of research objectives and the conclusive response to research question three affirm the overall success of the study.

Based on the research findings, the following recommendations can be made:

1. Implementation of Process Control Devices: Considering the significant positive impact on permeate flux and energy consumption rate, it is recommended that industrial processes employing ultrafiltration systems explore the implementation of process control devices can lead to substantial savings and improved efficiency.
2. Optimization of UF System Parameters: Utilising the developed mathematical equation and 3D plot to optimize UF system parameters, specifically feed pressure and energy consumption can help achieve the optimal UF performance as indicated by the research outcomes.
3. Continued Monitoring and Analysis: Maintaining a continuous monitoring system for UF processes to assess the ongoing impact of process control devices. Regular analysis can identify any changes or improvements needed, ensuring sustained benefits over time.
4. Integration of Findings into Industrial Practices: Industries involved in permeate flux production through UF systems should consider integrating the research findings into their operational practices. This can lead to enhanced productivity and energy efficiency, contributing to both economic and environmental sustainability.
5. Further Research Opportunities: Exploring further research opportunities to expand the understanding of the interrelation between feed pressure, flux, and energy consumption

in UF systems could involve investigating additional variables or applying the findings to different industrial contexts.

6. Collaboration and Knowledge Sharing: Encourage collaboration and knowledge sharing among researchers, industries, and policymakers to facilitate the widespread adoption of best practices derived from this research. This can contribute to broader advancements in the field and the adoption of sustainable technologies.

These recommendations aim to guide practical applications of the research outcomes, fostering a positive impact on industrial processes utilizing ultrafiltration systems.

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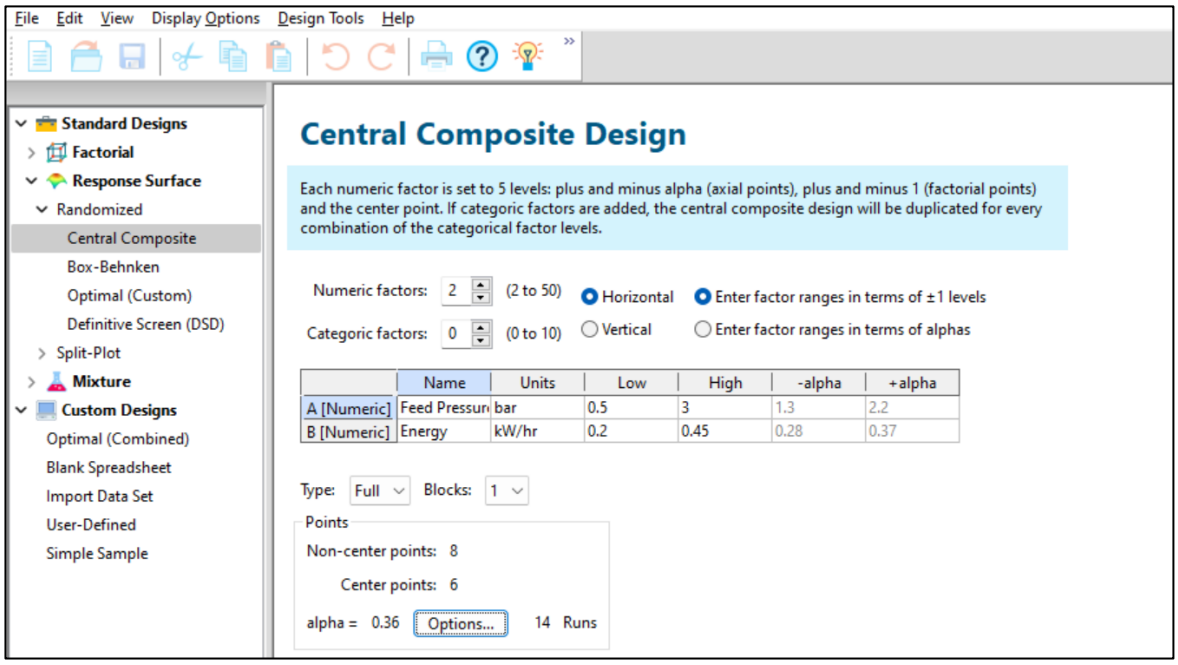
APPENDICES

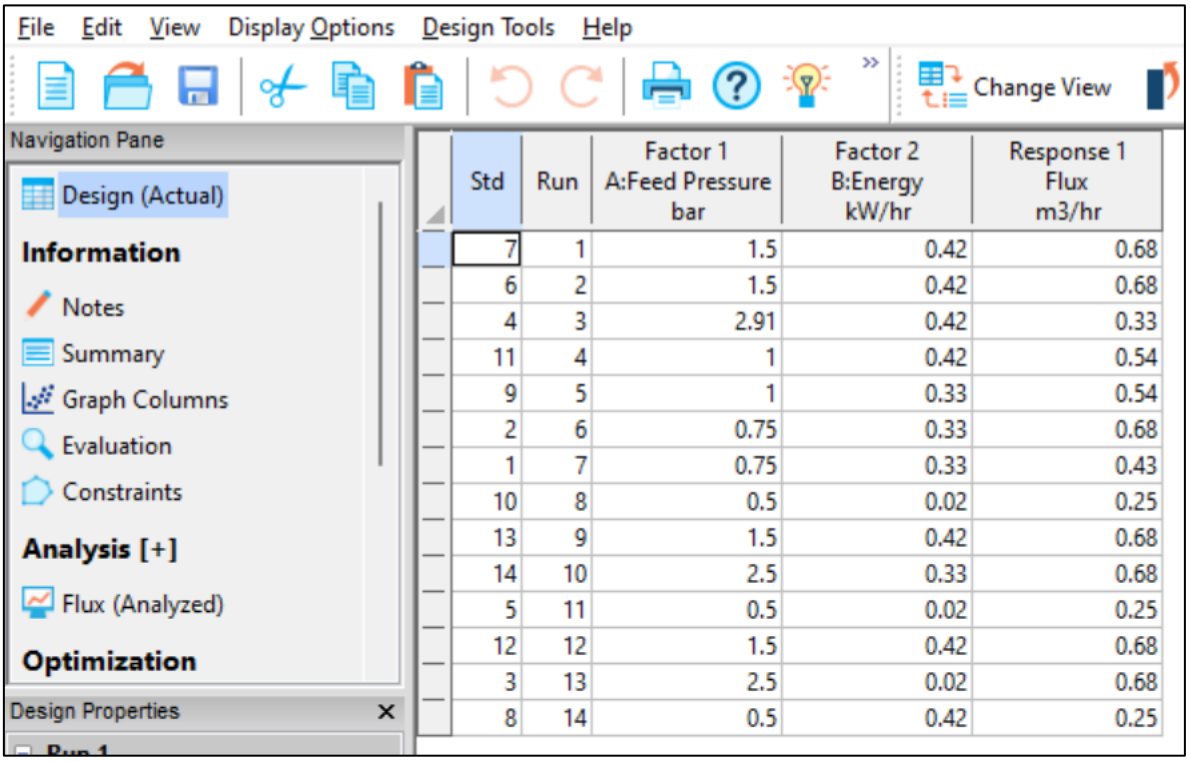
APPENDIX A: Central Composite Design



Appendix 4.1: Data for Center Point and Surface Response

The Appendix 4.1 was the data input to establish the surface response of permeate flux under two variables such as Feed Pressure and Energy Consumption. The operational inputs were set accordingly to the experiment set up and runs for 1 day. With 2 Numeric factors, the total runs were 14 and the center point for surface response was 6 while non-center points was 14 with α at 0.36.

APPENDIX B: Tabulated Data for Independent And Dependent Variable



Std	Run	Factor 1 A:Feed Pressure bar	Factor 2 B:Energy kW/hr	Response 1 Flux m3/hr
7	1	1.5	0.42	0.68
6	2	1.5	0.42	0.68
4	3	2.91	0.42	0.33
11	4	1	0.42	0.54
9	5	1	0.33	0.54
2	6	0.75	0.33	0.68
1	7	0.75	0.33	0.43
10	8	0.5	0.02	0.25
13	9	1.5	0.42	0.68
14	10	2.5	0.33	0.68
5	11	0.5	0.02	0.25
12	12	1.5	0.42	0.68
3	13	2.5	0.02	0.68
8	14	0.5	0.42	0.25

Appendix 4.2: Tabulated Data for DOE

The Appendix 4.2 was output for 14 runs of variable with response accordingly to the low and high variable set up. The highest and lowest permeate flux response was at 0.25 m^3/hr and 0.68 m^3/hr for Feed Pressure and Energy respectively.

APPENDIX C: Quadratic Model and Coefficients Table

ANOVA for Quadratic model

Response 1: Flux

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.3980	5	0.0796	14.29	0.0008	significant
A-Feed Pressure	0.0038	1	0.0038	0.6766	0.4346	
B-Energy	0.0306	1	0.0306	5.49	0.0472	
AB	0.0077	1	0.0077	1.38	0.2747	
A^2	0.1947	1	0.1947	34.96	0.0004	
B^2	0.0238	1	0.0238	4.28	0.0724	
Residual	0.0446	8	0.0056			
Lack of Fit	0.0133	3	0.0044	0.7099	0.5864	not significant
Pure Error	0.0313	5	0.0063			
Cor Total	0.4426	13				

Factor coding is **Coded**.
Sum of squares is **Type III - Partial**

The **Model F-value** of 14.29 implies the model is significant. There is only a 0.08% chance that an F-value this large could occur due to noise.

P-values less than 0.0500 indicate model terms are significant. In this case B, A^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

The **Lack of Fit F-value** of 0.71 implies the Lack of Fit is not significant relative to the pure error. There is a 58.64% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Appendix 4.3(a): Data for Significance Study on Operational Impact

Complementary to Power: Beta is complementary to statistical power (1 - Power). Power is the probability of correctly rejecting a false null hypothesis (i.e., not making a Type II error). Therefore:

Alpha = 1 – β

β = 1- Alpha (Energy 0.0403<0.05)

β = 0.9597

Coefficients Table

p-value shading: **p < 0.05** 0.05 ≤ p < 0.1 p ≥ 0.1

	Intercept	A	B	AB	A^2	B^2
Flux	0.80715	0.0293394	**-0.111713**	-0.0294408	**-0.417666**	-0.0521729
p-values		0.4346	**0.0472**	0.2747	**0.0004**	0.0724

Appendix 4.3(b): Operational Coefficients Table

APPENDIX D: Fit Statistic

Fit Statistics

Std. Dev.	0.0746		**R^2**	0.8993
Mean	0.5250		**Adjusted R^2**	0.8364
C.V. %	14.22		**Predicted R^2**	0.7803
			Adeq Precision	8.7843

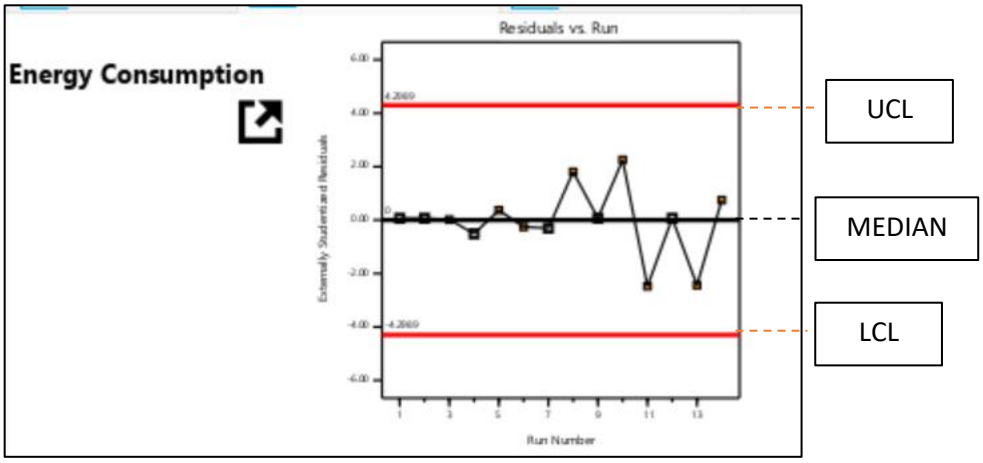
The **Predicted R^2** of 0.7803 is in reasonable agreement with the **Adjusted R^2** of 0.8364; i.e. the difference is less than 0.2.

Adeq Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 8.784 indicates an adequate signal. This model can be used to navigate the design space.

Appendix 4.4: Coefficient of Fit Statistic

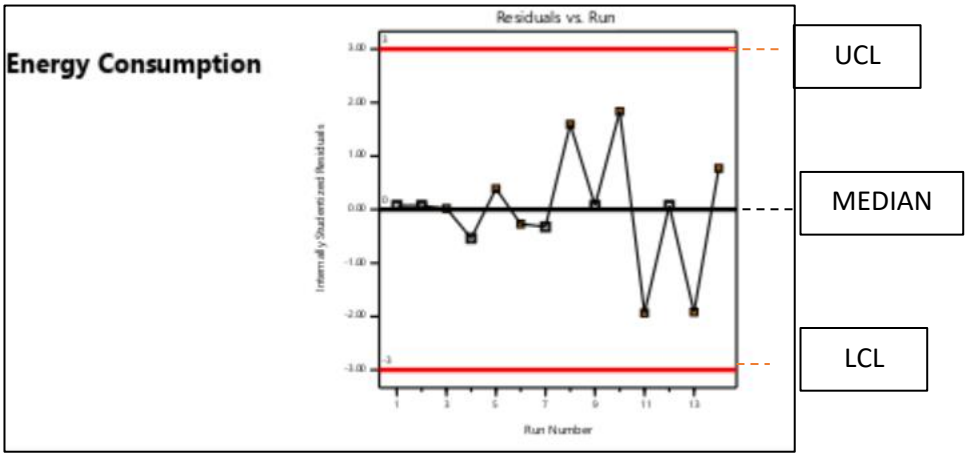
The Appendix 4.4 presented the significant effect of factors toward biogas production. The factors were examined to have no significant effect on biogas production. However, the factors did contribute on biogas as the recovered POME to biogas was at 52.32 % and 47.68 % was not recovered to biogas. The minimal effect found due the low range of factors applied and adjusted to test the biogas production.

APPENDIX E: Studentized Residuals



Appendix 4.5 (a): External Studentized Residuals

`



Appendix 4.5 (b): Internal Studentized Residuals

Appendix 4.6: Model Validation for Input Factors

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals
1	0.4200	0.4124	0.0076	0.218	0.075	0.070
2	0.4200	0.4124	0.0076	0.218	0.075	0.070
3	0.4200	0.4194	0.0006	0.943(1)	0.023	0.022
4	0.4200	0.4731	-0.0531	0.255	-0.536	-0.510
5	0.3300	0.2937	0.0363	0.353	0.393	0.371
6	0.0000	0.0092	-0.0092	0.911(1)	-0.269	-0.252
7	0.4200	0.4497	-0.0297	0.354	-0.322	-0.303
8	0.3300	0.1899	0.1401	0.415	1.594	1.804
9	0.4200	0.4124	0.0076	0.218	0.075	0.070
10	0.3300	0.1784	0.1516	0.483	1.834	2.253
11	0.0200	0.1899	-0.1699	0.415	-1.933	-2.478
12	0.4200	0.4124	0.0076	0.218	0.075	0.070
13	0.0200	0.1784	-0.1584	0.483	-1.917	-2.438
14	0.4200	0.3584	0.0616	0.517	0.771	0.749

Appendix 4.6 displays the diagnostic report statistics. It indicates that the residuals between the projected value and the actual value are dispersed over the data range of -0.0092 to 0.0616. This indicates that the assumption that the model's variance is constant and` not rejected, hence the model is dependable as Figure (). The range of leverage values is 0.218 to 0.911. In general, these values are excellent; a leverage value of 1 for a data point indicates that the residual will be zero. In other words, all experimental errors are accounted for in the model

APPENDIX F: Data Analysis for Model Development

Coefficients in Terms of Coded Factors

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	0.8071	1	0.0528	0.6853	0.9290	
A-Feed Pressure	0.0293	1	0.0357	-0.0529	0.1116	1.21
B-Energy	-0.1117	1	0.0477	-0.2217	-0.0018	8.85
AB	-0.0294	1	0.0251	-0.0873	0.0285	1.71
A^2	-0.4177	1	0.0706	-0.5806	-0.2548	1.65
B^2	-0.0522	1	0.0252	-0.1103	0.0060	8.50

The coefficient estimate represents the expected change in response per unit change in factor value when all remaining factors are held constant. The intercept in an orthogonal design is the overall average response of all the runs. The coefficients are adjustments around that average based on the factor settings. When the factors are orthogonal the VIFs are 1; VIFs greater than 1 indicate multi-colinearity, the higher the VIF the more severe the correlation of factors. As a rough rule, VIFs less than 10 are tolerable.

Appendix 4.6: Data on Model Optimization and Validation

Model optimization and validation shows the coefficient estimations represents the objective equation.

Objective Equation.

Y = A + α1 + α2 + = Intercept – A – B

Y (Output) = 3.02 – 0.4346 – 0.0472

A = 0.68 (Intercept)

α1 (Feed Pressure) = 0.4346 (Not Significant)

α2 (Energy) = 0.0472 (Significant)

P-value ≤ α: The association is statistically significant

If the P-value is less than or equal to the significance level, it can be concluded that there is a statistically significant association between the response variable and the term.

P-value > α: The association is not statistically significant

If the P-value is greater than the significance level, it cannot be concluded that there is a statistically significant association between the response variable and the term. The data may refit the model without the term.

APPENDIX H: Research Schedule

Table 3.10: Gantt Chart for Research Project

Month	Oct-21	Nov-21	Dec-21	Jan-22	Feb-22	Mac-22	April-22	May-22	Jun-22	July-22	Aug-22	Sept-22	Oct-22	Nov-22	Dec-22
CHAPTER 1 INTRODUCTION															
CHAPTER 2 LITERATURE REVIEW															
CHAPTER 3 RESEARCH METHODOLOGY															
CHAPTER 4 RESEARCH FINDING AND DISCUSSION															
CHAPTER 5 DISCUSSION AND CONCLUSION															
PROPOSAL DEFEND															
PRELIMINERIES THESIS															
THESIS															
EXTERNAL EXAMINER															

Month	Jan-23	Feb-23	Mac-23	April-23	May-23	Jun-23	July-23	Aug-23	Sept-23	Oct-23	Nov-23	Dec-23
CHAPTER 1 INTRODUCTION												
CHAPTER 2 LITERATURE REVIEW												
CHAPTER 3 RESEARCH METHODOLOGY												
CHAPTER 4 RESEARCH FINDING AND DISCUSSION												
CHAPTER 5 DISCUSSION AND CONCLUSION												
PROPOSAL DEFEND												
PRELIMINERIES THESIS												
THESIS												
EXTERNAL EXAMINER												

Appendix I: Flow Diagram of Research

The research framework of this research is elucidated by **Figure 1.1**.

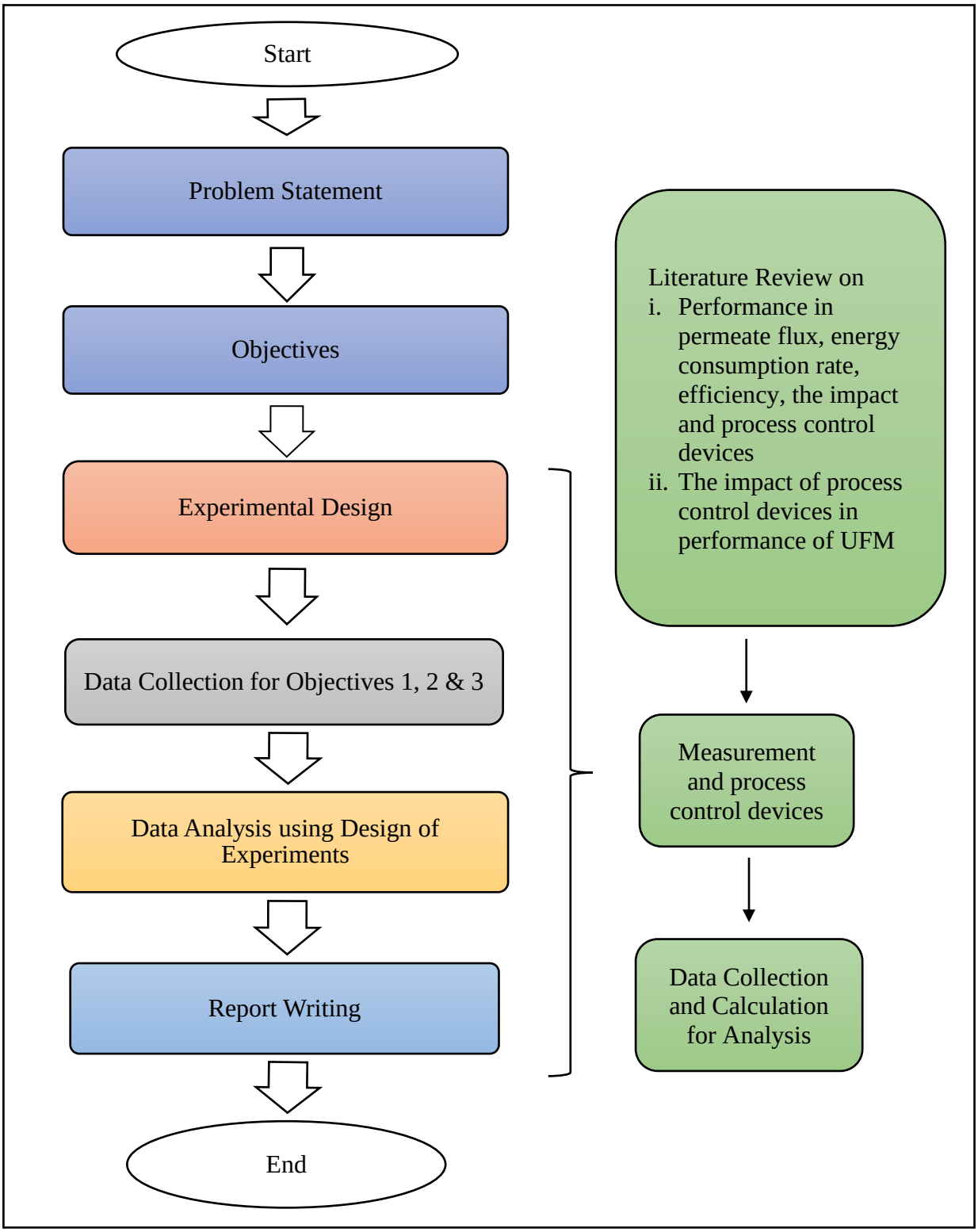


Figure 1.1: Framework of Research

Appendix J: Detail estimate for Pooled Standard Variance and Pooled t test for Objective 1

Calculate the pooled standard variance for two tailed tests:

$$S_p^2 = \frac{(n_1 - 1)\, S_1^2 + (n_2 - 1)\, S_2^2}{n_1 + n_2 - 2}$$

$$S_p^2 = \frac{(14 - 1) * 0.194^2 + (14 - 1) * 0.038^2}{14 + 14 - 2}$$

$$= 0.019$$

$$S_p = \sqrt{0.019}$$

$$= 0.14$$

Appendix K: Detail estimate for Pooled t test for Objective 1

Calculate the t estimate for two tailed tests:

$$t_{st} = \frac{X_2 - X_1}{\sqrt{Sp^2[\frac{1}{N1} + \frac{1}{N2}]}}$$

$$= \frac{0.958 - 0.692}{\sqrt{(0.019)[\frac{1}{14} + \frac{1}{14}]}}$$

$$= 5.039$$

Appendix L: Detail estimate for Pooled Standard Variance and Pooled t test for Objective 2

Calculate the pooled standard variance for two tailed tests:

$$S_p^2 = \frac{(n_1 - 1)\, S_1^2 + (n_2 - 1)\, S_2^2}{n_1 + n_2 - 2}$$

$$S_p^2 = \frac{(14 - 1) * 0.011^2 + (14 - 1) * 0.154^2}{14 + 14 - 2}$$

$$= 0.012$$

$$S_p = \sqrt{0.012}$$

$$= 0.109$$

Appendix M: Detail estimate for Pooled t test for Objective 2

Calculate the t estimate for two tailed tests:

$$t_{st} = \frac{X_1 - X_2}{\sqrt{Sp^2[\frac{1}{N1} + \frac{1}{N2}]}}$$

$$= \frac{0.551 - 0.364}{\sqrt{(0.012)[\frac{1}{14} + \frac{1}{14}]}}$$

$$= 4.45$$

Appendix N: t Table for critical value for Objective 1 and Objective 2

t value (as critical value) from table at two tailed and 0.05
Degree of Freedom,

$df = N_1 + N_2 - 2$
$= 14 + 14 - 2$
$= 26$

t Table

cum. prob	$t_{.50}$	$t_{.75}$	$t_{.80}$	$t_{.85}$	$t_{.90}$	$t_{.95}$	$t_{.975}$	$t_{.99}$	$t_{.995}$	$t_{.999}$	$t_{.9995}$
one-tail	0.50	0.25	0.20	0.15	0.10	0.05	0.025	0.01	0.005	0.001	0.0005
two-tails	1.00	0.50	0.40	0.30	0.20	0.10	0.05	0.02	0.01	0.002	0.001
df											
1	0.000	1.000	1.376	1.963	3.078	6.314	12.71	31.82	63.66	318.31	636.62
2	0.000	0.816	1.061	1.386	1.886	2.920	4.303	6.965	9.925	22.327	31.599
3	0.000	0.765	0.978	1.250	1.638	2.353	3.182	4.541	5.841	10.215	12.924
4	0.000	0.741	0.941	1.190	1.533	2.132	2.776	3.747	4.604	7.173	8.610
5	0.000	0.727	0.920	1.156	1.476	2.015	2.571	3.365	4.032	5.893	6.869
6	0.000	0.718	0.906	1.134	1.440	1.943	2.447	3.143	3.707	5.208	5.959
7	0.000	0.711	0.896	1.119	1.415	1.895	2.365	2.998	3.499	4.785	5.408
8	0.000	0.706	0.889	1.108	1.397	1.860	2.306	2.896	3.355	4.501	5.041
9	0.000	0.703	0.883	1.100	1.383	1.833	2.262	2.821	3.250	4.297	4.781
10	0.000	0.700	0.879	1.093	1.372	1.812	2.228	2.764	3.169	4.144	4.587
11	0.000	0.697	0.876	1.088	1.363	1.796	2.201	2.718	3.106	4.025	4.437
12	0.000	0.695	0.873	1.083	1.356	1.782	2.179	2.681	3.055	3.930	4.318
13	0.000	0.694	0.870	1.079	1.350	1.771	2.160	2.650	3.012	3.852	4.221
14	0.000	0.692	0.868	1.076	1.345	1.761	2.145	2.624	2.977	3.787	4.140
15	0.000	0.691	0.866	1.074	1.341	1.753	2.131	2.602	2.947	3.733	4.073
16	0.000	0.690	0.865	1.071	1.337	1.746	2.120	2.583	2.921	3.686	4.015
17	0.000	0.689	0.863	1.069	1.333	1.740	2.110	2.567	2.898	3.646	3.965
18	0.000	0.688	0.862	1.067	1.330	1.734	2.101	2.552	2.878	3.610	3.922
19	0.000	0.688	0.861	1.066	1.328	1.729	2.093	2.539	2.861	3.579	3.883
20	0.000	0.687	0.860	1.064	1.325	1.725	2.086	2.528	2.845	3.552	3.850
21	0.000	0.686	0.859	1.063	1.323	1.721	2.080	2.518	2.831	3.527	3.819
22	0.000	0.686	0.858	1.061	1.321	1.717	2.074	2.508	2.819	3.505	3.792
23	0.000	0.685	0.858	1.060	1.319	1.714	2.069	2.500	2.807	3.485	3.768
24	0.000	0.685	0.857	1.059	1.318	1.711	2.064	2.492	2.797	3.467	3.745
25	0.000	0.684	0.856	1.058	1.316	1.708	2.060			3.450	3.725
26	0.000	0.684	0.856	1.058	1.315	1.706	2.056			3.435	3.707
27	0.000	0.684	0.855	1.057	1.314	1.703	2.052	2.473	2.771	3.421	3.690
28	0.000	0.683	0.855	1.056	1.313	1.701	2.048	2.467	2.763	3.408	3.674
29	0.000	0.683	0.854	1.055	1.311	1.699	2.045	2.462	2.756	3.396	3.659
30	0.000	0.683	0.854	1.055	1.310	1.697	2.042	2.457	2.750	3.385	3.646
40	0.000	0.681	0.851	1.050	1.303	1.684	2.021	2.423	2.704	3.307	3.551
60	0.000	0.679	0.848	1.045	1.296	1.671	2.000	2.390	2.660	3.232	3.460
80	0.000	0.678	0.846	1.043	1.292	1.664	1.990	2.374	2.639	3.195	3.416
100	0.000	0.677	0.845	1.042	1.290	1.660	1.984	2.364	2.626	3.174	3.390
1000	0.000	0.675	0.842	1.037	1.282	1.646	1.962	2.330	2.581	3.098	3.300
z	0.000	0.674	0.842	1.036	1.282	1.645	1.960	2.326	2.576	3.090	3.291
	0%	50%	60%	70%	80%	90%	95%	98%	99%	99.8%	99.9%
	Confidence Level										

tc = 2.056