

HEAT EXCHANGER FOULING ESTIMATION AND PREDICTION

BY

Mohammed Ahmed Mohammed Eltoum Mohammed Ali

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

SYSTEMS AND CONTROL ENGINEERING

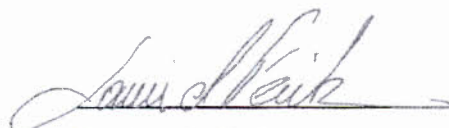
April 2020

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **Mohammed Ahmed Mohammed Eltoum Mohammed Ali** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN SYSTEMS & CONTROL ENGINEERING**.



Dr. Sami El-Ferik
(Advisor)



Dr. Hesham EL-Fares
Department Chairman



Dr. Fouad M. Al-Sunni
(Member)



Dr. Suliman S. Al-Homidan
Dean of Graduate Studies



Dr. Rached Ben-Mansour
(Member)



Date

© **Mohammed Ahmed Mohammed Eltoum Mohammed Ali**

2020

To my beloved family

ACKNOWLEDGMENTS

First and foremost, I would like to praise Allah almighty for providing me the patience and knowledge to pursue this research and complete it.

I would like to thank my advisor, Dr. Sami El-Ferik, for his unreserved and invaluable support, guidance, and encouragement, as well as his remarkable inspiration and suggestions. Also, I would like to acknowledge the invaluable assistance I got from my committee members, Dr. Fouad AL-Sunni, for his support and valuable comments, and Dr. Rached Ben-Mansour for his precious time and consultation where his model represents the building block for this thesis. Moreover, I would like to express my gratitude to Dr. Mustafa Al-Naser, R&D manager at Yokogawa Saudi Arabia Company, for his valuable help and contribution to developing the fouling estimation and prediction models.

Finally, I would like to forward my deepest gratitude to the whole KFUPM community

TABLE OF CONTENTS

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS	VI
LIST OF TABLES	VIII
LIST OF FIGURES	IX
NOMENCLATURE.....	XI
ABSTRACT.....	XV
ملخص الرسالة	XVII
CHAPTER 1 INTRODUCTION.....	1
1.1 Heat Exchanger Classifications.....	1
1.2 Fouling in Heat Exchangers	2
1.3 Types of Fouling	4
1.4 General Model of Fouling	5
1.5 Objectives.....	6
1.6 Methodology.....	7
1.7 Thesis Organization.....	8
CHAPTER 2 LITERATURE REVIEW	9
2.1 Fouling Estimation and Prediction Models	9
2.2 Fouling Compensation	15
CHAPTER 3 DOUBLE PIPE HEAT EXCHANGER MODELLING	19
3.1 Introduction	19
3.2 Thermal Dynamic Model of The Double Pipe Heat Exchanger	21
3.3 Double Pipe Heat Exchanger Inner Pipe Pressure Drop	23
3.4 Fouling Effect	25
3.5 Numerical Simulation.....	25

CHAPTER 4 HEAT EXCHANGER FOULING ESTIMATION AND PREDICTION	35
4.1 Introduction	35
4.2 Artificial Neural Networks.....	35
4.3 Long Short-Term Memory (LSTM)	37
4.4 Results and Discussion	39
4.5 Conclusion.....	45
CHAPTER 5 HEAT EXCHANGER FOULING COMPENSATION.....	46
5.1 Introduction	46
5.2 PID Parameters Optimization Using Harmony Search Algorithm	46
5.3 Fuzzy Logic Controller	51
5.4 Results and Discussion	56
5.4.1 The Operation Under Standard Conditions	58
5.4.2 Varying Inner Pipe Outlet Temperature Setpoint.....	60
5.4.3 Varying Inner Pipe Inlet Flow Rate.....	63
5.4.4 Varying Inlet Temperatures	66
5.4.5 Fouling Build-Up.....	69
5.4.6 Measurement Noise.....	71
5.5 Concluding Remarks.....	74
CHAPTER 6 CONCLUSION AND FUTURE WORK.....	75
6.1 Conclusion.....	75
6.2 Future Work	76
REFERENCES.....	77
VITAE.....	81

LIST OF TABLES

Table 2. 1: Crude Oil Fouling Prediction Models.....	10
Table 3. 1: Heat Exchanger Parameters.....	26
Table 4. 1:The Parameters of Simulated DPHE	40
Table 5. 1: FLC Rules.....	54
Table 5. 2: Fuzzy Tuning System Rules	56
Table 5. 3: PID Optimized parameters	57

LIST OF FIGURES

Figure 1. 1: Flow arrangement: (a) parallel flow , (b) counter flow , and (c) cross-flow[1]	2
Figure 1. 2: Temperature distribution of fouled heat exchanger[3].....	3
Figure 1. 3: Asymptotic fouling.....	6
Figure 2. 1: Nonlinear observer	11
Figure 2. 2: Implementation of a lock-in technique[22].	13
Figure 2. 3: Elman neural network architecture[27]	15
Figure 2. 4: Simulink model of the heat exchangers and PID controller[28].....	16
Figure 2. 5 : Robust MPC with integral action control architecture[30].....	17
Figure 2. 6: PID controlled HEN scheme[31].	18
Figure 3. 1: Parallel flow heat exchanger	19
Figure 3. 2: Counter flow heat exchanger.....	20
Figure 3. 3: Cross-section view of the double pipe heat exchanger	20
Figure 3. 4: Parallel flow DPHE outlet temperatures	28
Figure 3. 5: Parallel flow DPHE pressure drop	28
Figure 3. 6 : Parallel flow outlet temperatures gradient at different simulation times	29
Figure 3. 7: Parallel flow DPHE steady state temperature gradient	29
Figure 3. 8: Counter flow DPHE outlet temperatures.....	30
Figure 3. 9: Counter flow DPHE pressure drop.....	30
Figure 3. 10: Counter flow DPHE Outlet temperatures gradient at different simulation times.....	31
Figure 3. 11:Parallel flow DPHE Steady-state temperature gradient	31
Figure 3. 12: Inner pipe fouling resistance	32
Figure 3. 13: Parallel flow DPHE outlet temperatures under fouling build-up.	33
Figure 3. 14: Parallel flow DPHE inner pipe pressure drop under fouling build-up.....	33
Figure 3. 15: Counter flow DPHE outlet temperatures under fouling build-up.	34
Figure 3. 16: Counter flow DPHE inner pipe pressure drop under fouling build-up.	34
Figure 4. 1:ANN underlying architecture	36
Figure 4. 2: ANN estimation model.....	37
Figure 4. 3: LSTM block	38
Figure 4. 4: The proposed model architecture	39
Figure 4. 5: Inner pipe fouling curve	41
Figure 4. 6: Counter flow DPHE inner pipe pressure drop.....	41
Figure 4. 7: Counter flow DPHE open-loop response	42
Figure 4. 8: Training performance	43
Figure 4. 9: ANN regression performance.....	43

Figure 4. 10: The LSTM training performance	44
Figure 4. 11: Fouling prediction performance	45
Figure 5. 1: PID controlled DPHE block diagram.....	47
Figure 5. 2: Harmony search algorithm flowchart.....	50
Figure 5. 3: Fuzzy logic control system structure.....	51
Figure 5. 4: The proposed FLC architecture	52
Figure 5. 5: Inputs' membership functions.....	53
Figure 5. 6: Output's membership functions	53
Figure 5. 7: FLC internal structure	54
Figure 5. 8: input and output membership functions of adaption speed fuzzy tuner.....	55
Figure 5. 9: HSA convergence.....	57
Figure 5. 10: Hot fluid outlet temperature under standard conditions.....	58
Figure 5. 11: Cold fluid mass flow rate under standard conditions (PID).....	59
Figure 5. 12: Cold fluid mass flow rate under standard conditions (Fuzzy).....	59
Figure 5. 13: Cold fluid outlet temperature under standard conditions	60
Figure 5. 14: Hot fluid outlet temperature under varying setpoint	61
Figure 5. 15: Cold fluid mass flow rate under varying setpoint (PID)	61
Figure 5. 16: Cold fluid mass flow rate under varying setpoint (Fuzzy).....	62
Figure 5. 17: Cold fluid outlet temperature under varying setpoint	62
Figure 5. 18: Hot fluid mass flowrate	63
Figure 5. 19: Hot fluid outlet temperature under varying mass flow rate.....	64
Figure 5. 20: Cold fluid mass flow rate under varying hot fluid mass flow rate (PID).....	64
Figure 5. 21: Cold fluid mass flow rate under varying hot fluid mass flow rate (Fuzzy)..	65
Figure 5. 22: Cold fluid outlet temperature under varying hot fluid mass flow rate	65
Figure 5. 23: Inlet temperatures	66
Figure 5. 24: Hot fluid outlet temperature under varying inlet temperatures	67
Figure 5. 25: Cold fluid mass flow rate under varying inlet temperatures (PID)	67
Figure 5. 26: Cold fluid mass flow rate under varying inlet temperatures (fuzzy).....	68
Figure 5. 27: Cold fluid outlet temperature under varying inlet temperatures	68
Figure 5. 28: Hot fluid outlet temperature under fouling build-up	69
Figure 5. 29: Cold fluid mass flowrate under fouling build-up (PID)	70
Figure 5. 30: Cold fluid mass flowrate under fouling build-up (Fuzzy).....	70
Figure 5. 31: Cold fluid outlet temperature under fouling build-up	71
Figure 5. 32: injected noise	72
Figure 5. 33: Hot fluid outlet temperature under output noise.	72
Figure 5. 34: cold fluid mass flow rate under output noise (PID).	73
Figure 5. 35: cold fluid mass flow rate under output noise (Fuzzy)	73
Figure 5. 36: Cold fluid outlet temperature under output noise.....	74

Nomenclature

A	Heat transfer area (m^2).
b_i	LSTM input gate bias
b_f	LSTM forget gate bias
b_o	LSTM output gate weight bias
C_{P_h}	Specific heat at a constant pressure of the hot fluid.
C_{P_c}	Specific heat at a constant pressure of the cold fluid.
C_t	LSTM cell state
D_i	Inner diameter of the heat exchanger outer pipe(m).
D_o	Outer diameter of the heat exchanger outer pipe(m).
d_i	Inner diameter of the heat exchanger inner pipe(m).
d_{ia}	Actual inner diameter of the heat exchanger inner pipe(m).
d_o	Outer diameter of the heat exchanger inner pipe(m).
$\dot{E}_{in}$	Energy transfer rate at heat exchanger inlet (W).
$\dot{E}_{out}$	Energy transfer rate at heat exchanger outlet (W).
$\dot{E}_s$	Rate of change in stored energy (W)
F	Logarithmic mean temperature difference correction factor.
f	Darcy friction factor.
h	Neuron output
i	Spatial index.
K_1, K_2	constants

k_f	Thermal conductivity of fouling material (W/m .K).
K_p	Proportional gain
K_i	Integral gain
K_d	Derivative gain
L	Length of heat exchanger pipe (m).
M	Number of heat exchanger segments.
$\dot{m}_h$	Hot fluid mass flow rate (Kg/sec).
$\dot{m}_c$	Cold fluid mass flow rate (Kg/sec).
N	Number of samples
Q	Heat transfer rate (W).
Re	Reynold number.
R_{fa}	Fouling resistance per unit area ($\frac{K}{W}$)
R_f	Fouling resistance ($\frac{m^2.K}{W}$)
$T_{h_{in}(t)}$	Hot side inlet temperature ($^{\circ}C$)
$T_{h_{out}(t)}$	Hot side outlet temperature($^{\circ}C$)
$T_{c_{in}(t)}$	Cold side inlet temperature($^{\circ}C$)
$T_{c_{out}(t)}$	Cold side outlet temperature($^{\circ}C$)
T_s	Sampling time (second)
U	Overall heat transfer coefficient (W/m ² .K).
U_c	Overall heat transfer coefficient of a clean heat exchanger (W/m ² .K).
U_f	Overall heat transfer coefficient of a fouled heat exchanger(W/m ² .K).

U_{mi}	Dynamic velocity of the heat exchanger inner pipe fluid (m/s).
u_t	Controller output
W	Weight vector
W_i	LSTM input gate weight matrix
W_f	LSTM forget gate weight matrix
W_o	LSTM output gate weight matrix
x_1	Thickness of hot fluid fouling pipe layer (m)
x_2	Thickness of cold fluid fouling pipe layer (m)
x_{ft}	Thickness of the foulant layer at time t
x_m	Thickness of heat exchanger wall (m)
X	Neuron input
X_t	LSTM input vector
z	A backward shift operator
ΔA_s	The change in the surface area (m^2).
ΔP	Pressure drop
ΔT_{LMTD}	Logarithmic mean temperature difference.
Δt	Time step (second).
ΔV_1	The change in the inner pipe volume (m^3).
ΔV_2	The change in the outer pipe volume (m^3).
Δx	Length of each heat exchanger segment (m).
λ_1	Thermal conductivity of hot fluid pipe fouling layer (W/m .K)
λ_2	Thermal conductivity of cold fluid pipe fouling layer (W/m .K)

λ_m	Thermal conductivity of heat exchanger wall (W/m .K)
α_1	Convective heat transfer coefficient of hot fluid (W/m ² .K).
α_2	Convective heat transfer coefficient of cold fluid (W/m ² .K).
ϕ_D	Deposition rate
ϕ_R	Removal rate
ρ_h	Hot fluid density (Kg/m ³).
ρ_c	Cold fluid density (Kg/m ³).
μ	Dynamic viscosity (N.s/m ²)
σ	Sigmoid activation function
α	Fuzzy controller output gain
ϵ	Uniformly distributed random number

ABSTRACT

Full Name : [Mohammed Ahmed Mohammed Eltoum Mohammed Ali]

Thesis Title : [Heat Exchanger Fouling Estimation and Prediction]

Major Field : [Systems and Control Engineering]

Date of Degree : [April 2020]

Heat exchangers are indispensable components in most modern industrial systems, especially in power generation and the oil industry sectors. Fouling is the accumulation of undesired materials on the inner surface of a heat exchanger, producing a rise in thermal resistance and consequent decline in thermal efficiency. Fouling deposition in heat exchangers is one of the most challenging problems that affect industrial plants efficiency and raise production cost, also fouling results in an increment of greenhouse gases, which severely affect the earth's ecological system.

This research aims to develop a fouling estimation model using a data-driven approach for a double pipe heat exchanger based on outlet temperatures, and pressure drop data that can be obtained from the field instruments related to the targeted heat exchanger. Artificial neural networks (ANN) is one of the dominant techniques in data-driven model's domain due to their capability in modelling systems that experience a highly nonlinear and complex dynamics such as heat exchanger subjected to fouling build-up.

This research also targets fouling prediction, which gives more flexibility in management and operation planning level that can help to no small extent in maintenance scheduling and avoiding unplanned shutdowns. Furthermore, the compensation of fouling thermal

effects on the stream outlet temperature has been addressed by employing different feedback control schemes.

The obtained results showed high accuracy in terms of both fouling estimation and prediction. Also, the proposed control schemes successfully compensate fouling effect on the heat exchanger stream outlet temperature.

ملخص الرسالة

الاسم الكامل: محمد احمد محمد التوم محمد علي

عنوان الرسالة: الكشف والتنبؤ بالترسبات في المبادل الحراري

التخصص: هندسة النظم والتحكم

تاريخ الدرجة العلمية: [ابريل 2020]

تعتبر المبادلات الحرارية احدى المكونات التي لا يمكن الاستغناء عنها في معظم الأنظمة الصناعية الحديثة ، خاصة في توليد الطاقة وقطاعات صناعة النفط. الترسبات هي تراكم المواد غير المرغوب فيها على السطح الداخلي للمبادل حراري ، مما ينتج عنه ارتفاع في المقاومة الحرارية وما ينتج عن ذلك من انخفاض في الكفاءة الحرارية. يعد ترسيب المواد المسببة للترسبات في المبادلات الحرارية من أكثر المشاكل صعوبة التي تؤثر على كفاءة المنشآت الصناعية وتزيد من تكلفة الإنتاج ، كما ينتج عن ذلك زيادة في غازات الدفينة التي تؤثر بشدة على النظام البيئي للأرض. يهدف هذا البحث إلى تطوير نموذج تقدير للترسبات باستخدام نهج قائم على البيانات لمبادل حراري يعتمد على بيانات درجات الحرارة وانخفاض الضغط التي يمكن الحصول عليها من الأدوات الميدانية المتعلقة بالمبادل الحراري المستهدف. الشبكات العصبية الاصطناعية (ANN) هي واحدة من التقنيات السائدة في مجال النموذج المستند إلى البيانات بسبب قدرتها في نمذجة الأنظمة التي تواجه ديناميكيات غير خطية ومعقدة للغاية مثل المبادل الحراري الذي يتعرض لتراكم الترسبات. يهدف هذا البحث أيضاً إلى التنبؤ بالترسب ، مما يمنح مزيداً من المرونة في مستوى التخطيط الإداري والتشغيلي الذي يمكن أن يساعد إلى حد ما في جدولة الصيانة وتجنب عمليات الإغلاق غير المخطط لها. علاوة على ذلك ، تمت معالجة تعويض التأثيرات الحرارية الناتجة من الترسبات على درجة حرارة الخارجة عن طريق استخدام تفنيدات تحكم ذات تغذية مرتدة مختلفة. أظهرت النتائج التي تم الحصول عليها دقة عالية من حيث التقدير والتنبؤ بالترسبات. كما أن مخططات التحكم المقترحة تعوض بنجاح تأثير الترسبات على درجة حرارة مخرج المبادل الحراري.

CHAPTER 1

INTRODUCTION

Heat exchanger plays an essential role in a broad range of industrial applications where it facilitates heat transfer between two or multiple fluids. Heat exchanger enables the heat transfer process between two fluids that have different temperatures without direct contact between these fluids where heat is transferred by convection for each fluid and by conduction between fluids and the heat exchanger wall that separate them. Heat exchanger applications cover a broad range of industrial sectors, including petroleum industries, petrochemical sector, sewage treatment, and thermal power plants.

1.1 Heat Exchanger Classifications

Several variants of heat exchangers have been developed to meet the different requirements of industrial applications, and that led to the appearance of multiple classifications. Based on flow arrangement as demonstrated in figure 1.1, heat exchangers can be grouped as follows:

- **Parallel flow heat exchangers:** where the two fluids are in parallel to each other flowing in the same direction.
- **Counter flow heat exchangers:** they are similar to parallel flow type, but the fluids flow in opposite directions and considered as the most efficient type among the others.

- **Cross Flow heat exchangers:** in this type, the two fluids are perpendicular to each other's where both fluids are mixed, only one fluid is mixed, or both fluids are unmixed.

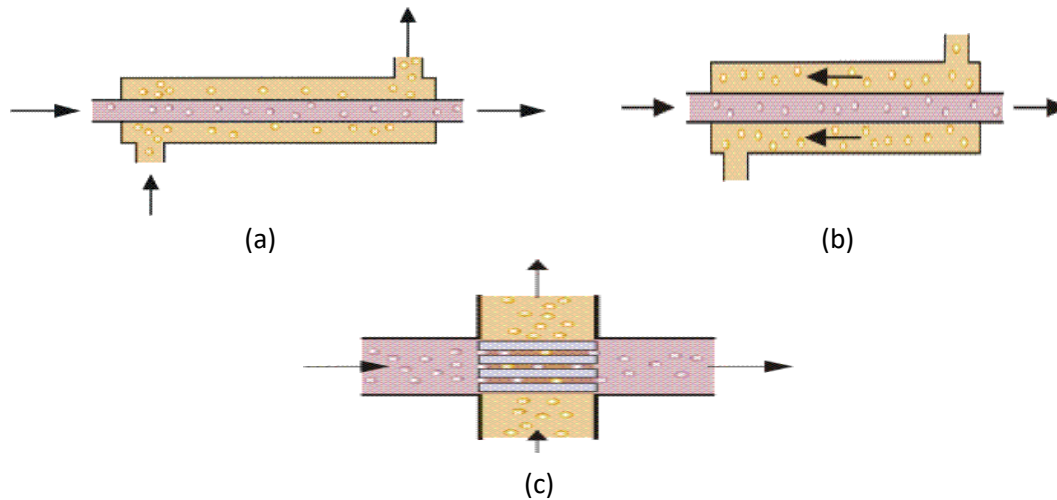


Figure 1. 1: Flow arrangement: (a) parallel flow , (b) counter flow , and (c) cross-flow[1]

Also, the heat exchanger can be classified according to the mechanism of heat transfer, construction, and pass arrangement.

Considering the heat transfer mechanism, the heat exchanger is classified as a condenser and evaporator, while based on the construction, it classified as tabular, plate, extended surface, and regenerators. Regarding pass arrangement, it classified as a single pass and a multi pass[2].

1.2 Fouling in Heat Exchangers

Fouling is the accumulation of undesired materials on the inner surface of a heat exchanger, producing a rise in thermal resistance and consequent decline in thermal efficiency. The foulant, which can either be organic or an inorganic material, usually has a poor thermal

conductivity compared to the metallic wall conductivity, which results in degradation of heat transfer rate.

Fouling formation can be described as a relation between deposit accumulation and removal rates. Figure 1.2 shows temperature distribution under the presence of fouling, where T1 and T6 denote the temperature of the hot and cold fluids, respectively[3].

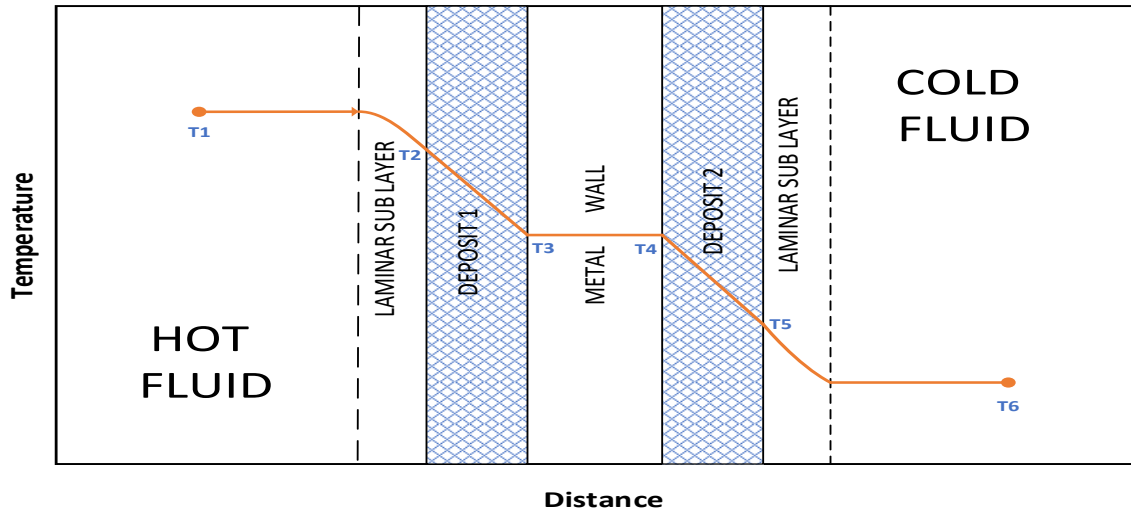


Figure 1. 2: Temperature distribution of fouled heat exchanger[3]

The heat transfer rate under steady-state conditions can be written as follows

$$Q = UA\Delta T_{LMTD}F \quad (1.1)$$

Where A is the area of heat transfer, U is the overall coefficient of heat transfer, ΔT_{LMTD} is the logarithmic mean temperature difference which is given by Equation (1.2), and F is the correction factor of LMTD.

$$\Delta T_{LMTD} = \frac{\Delta T_1 - \Delta T_2}{\log\left(\frac{\Delta T_1}{\Delta T_2}\right)} \quad (1.2)$$

Where ΔT_1 and ΔT_2 represent the temperature difference between hot and cold fluid at heat exchanger's inlet and outlet, subsequently.

For the fouled heat exchanger the overall heat transfer coefficient is given by

$$\frac{1}{U_f} = \left(\frac{x_1}{\lambda_1} \right) + \left(\frac{x_2}{\lambda_2} \right) + \frac{x_m}{\lambda_m} + \frac{1}{\alpha_1} + \frac{1}{\alpha_2} = R_T \quad (1.3)$$

Where x_1, x_2 , and x_m represent the thickness of deposit1, deposit2, and metallic wall respectively while λ_1, λ_2 , and λ_m represent the thermal conductivity of deposit1, deposit2, and metallic wall, respectively. α_1 is the convective heat transfer coefficient for the hot fluid while α_2 denotes the convective heat transfer coefficient for the cold fluid. R_T implies the total thermal resistance per unit area.

For the clean heat exchanger, U is given by

$$\frac{1}{U_C} = \frac{x_m}{\lambda_m} + \frac{1}{\alpha_1} + \frac{1}{\alpha_2} \quad (1.4)$$

Equation (1.4) illustrates the effect of fouling on the heat transfer coefficient, where the increase of deposits increases thermal resistance.

1.3 Types of Fouling

Given the fouling formation mechanism, fouling can be grouped into the following six classes[4].

- Scale fouling: is the common fouling type that is often related to certain salts such as calcium carbonate that naturally found in water. With the increase in temperature, these salts' solubility declines, which leads to deposits formation on the surface of the heat exchanger. It is hard to remove scale fouling using mechanical cleaning methods so that the use of chemical methods may be inevitable.

- Particulate fouling is the formation of an insulating layer due to the accumulation of certain particles (such as sand) on the heat exchanger inner surface.
- Corrosion fouling: appears owing to a chemical reaction involving the heat exchanger inner surface material, which results in a corrosion product that reduces the thermal conductivity.
- Chemical fouling: results from a chemical reaction within the fluid streams, which leads to a formation of deposits on the heat transfer inner surface.
- Frizzing fouling: happens due to reducing the temperature of the hot stream close to the freezing point of one of its components.
- Biological fouling: occurs due to the presence of biological organisms.

1.4 General Model of Fouling

According to Kern et al. [5], the rate of change in deposition mass could be defined as follows

$$\frac{dm}{dt} = \phi_D - \phi_R \quad (1.5)$$

Where m, ϕ_D, ϕ_R represent deposit mass, deposition rate, removal rate, respectively.

In the case of asymptotic fouling as depicted in Figure 1.3, fouling resistances per unit area (R_{fa}) is given by

$$R_{fa} = A(1 - e^{-\beta t}) \quad (1.6)$$

Where

A : is the fouling saturation value.

β : is a constant related to the properties of the system.

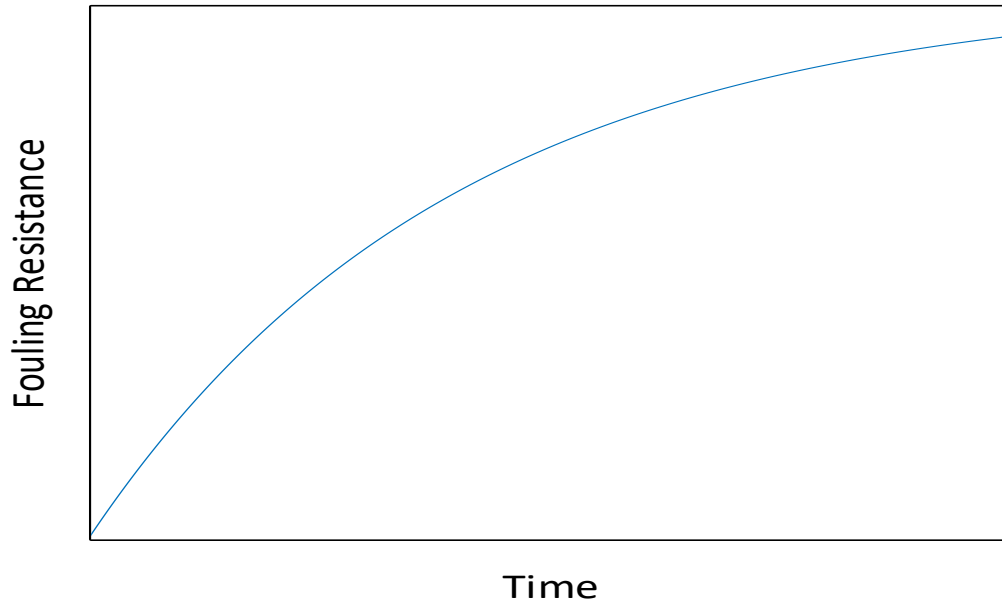


Figure 1. 3: Asymptotic fouling

1.5 Objectives

The general goal of this research is to estimate and predict heat exchanger fouling under a mono phase flow regime. The specific objectives are as follows:

1. Conduct and document an extensive literature survey about heat exchanger fouling estimation, prediction, and compensation.
2. Formulate a mathematical model for the fouled heat exchanger under both steady-state and transient conditions.
3. Develop a data-driven model for heat exchanger fouling estimation.
4. Develop a fouling prediction model that can be used for heat exchanger predictive maintenance.
- 5- Study the possibility of compensating fouling by using a proper control technique.

1.6 Methodology

This research consists of three parts. The first part is concerned with estimation or detection of fouling level in heat exchanger under different operating conditions where the estimation model detects fouling level based on the process measurements, mainly temperature, pressure drop measurements. The second part focus on predicting fouling in advance based on the current and past historical data of the fouling rate. The last part is intended to compensate for the fouling build-up thermal effect by using a feedback controller to suppress the fouling effect.

This study considers the counter flow double pipe heat exchanger type where the fouling occurs in the inner pipe of the heat exchanger. A numerical simulation model is to be developed for the double pipe heat exchanger considering both thermal and hydraulic characteristics. A data-driven approach based on machine learning techniques are adopted for the development of both estimation and prediction models. The inner pipe pressure drop and outlet temperatures beside the fouling represent the training data for the estimation model. The prediction model is based on the estimated fouling by training the model to learn the fouling trend using the available historical data in order to predict future trends. Regarding fouling compensation, two feedback control schemes are developed to manipulate the outer pipe mass flow rate in order to absorb fouling effects on the process variable, where the inner pipe outlet temperature has been selected as the process variable. MATLAB/SIMULINK used to simulate the double pipe heat exchanger, implementing and training the estimation and prediction models besides the realization of feedback controllers to compensate fouling.

1.7 Thesis Organization

The thesis is arranged in the following sequence

Chapter 1 establishes the general background about the thesis topic, thesis objectives, and methodology as well as thesis organization.

Chapter 2 contains a literature survey of fouling estimation and prediction techniques in addition to the review of fouling compensation methods.

Chapter 3 presents the dynamic modelling of a double pipe heat exchanger, including a fouling build-up effect on heat exchanger thermal and hydraulic characteristics.

Chapter 4 includes the fouling estimation and prediction based on data-driven models that detect and predict the fouling based on the heat exchanger measured variables.

Chapter 5 presents the fouling compensation by using two feedback control schemes to regulate the inner pipe outlet temperature in the vicinity of the desired value.

Chapter 6 concludes the thesis and lists some recommendations for possible future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Fouling Estimation and Prediction Models

Fouling rate models can be divided into three categories: the first category is deterministic models which are derived from the first principles, secondly semiempirical models which are based on the first principles with unknowns that estimated using a parameter estimation technique, and finally artificial intelligence models[6].

One of the early deterministic models to describe fouling is presented in 1959 by Kern et al. [5] where he stated that the rate of change in deposition mass could be defined as

$$\frac{dm}{dt} = \phi_D - \phi_R \quad (2.1)$$

Where m, ϕ_D, ϕ_R represent deposit mass, deposition rate, and removal rate, respectively.

Taking into consideration tubular flow pattern, the change in fouling thickness can be presented as

$$\frac{dx_f}{dt} = K_1 c M - K_2 \tau x_{ft} \quad (2.2)$$

where:

c is the concentration of fouling

M represents the mass flow rate.

K_1 and K_2 are real constants.

τ is the shear stress

x_{ft} is the thickness of the foulant layer at time t .

In equation (2.2) on the right side, the first term denotes the deposition rate while the second term denotes erosion or removal rate. Kern model is considered as a general model for fouling description, based on this approach, many models have been proposed [7]. Table 2.1 highlights some of these models, which are mainly developed for crude oil. A more detailed discussion can be found in [8] and [7].

Table 2. 1: Crude Oil Fouling Prediction Models

Model	Equation
Ebert and Panchal[9]	$\frac{dR_f}{dt} = \alpha Re^\beta \exp\left(-\frac{E}{R_g T_f}\right) - \gamma \tau_w$
Polley et al.[10]	$\frac{dR_f}{dt} = \alpha Re^{-0.8} Pr^{-0.33} \exp\left(-\frac{E}{R_g T_s}\right) - \gamma Re^{0.8}$
Nasr and Givi [11]	$\frac{dR_f}{dt} = \alpha Re^{-0.8} \exp\left(-\frac{E}{R_g T_f}\right) - \gamma Re^{0.4}$
Shetty et al.[12]	$\frac{dR_f}{dt} = \alpha Re^\beta Pr^{-0.33} \exp\left(\frac{-E}{RT_{eff}}\right) - \gamma \tau_w$ $T_{eff} = \alpha_1 T_{so} + \alpha_2 T_b$

The parameters (α , β , E , γ) are to be chosen according to specifications of crude oil[13]

Markowski et al.[14] presented an algorithm for the determination of fouling resistance. The algorithm applied for two series-connected shell and tube heat exchangers, where the least square method used to adjust the parameters of surface film conductance given in equation (2.3).

$$Nu = C \cdot Re^a Pr^b (Pr/Pr_w)^o \quad (2.3)$$

This method requires that the data of mass flow rate, temperature, pressure, and thermophysical properties are continuously available. The objective functions to be minimized is defined as the difference between the outlet temperatures obtained from the mathematical model and the measured temperatures as written in equation (2.4).

$$\text{Objective Function} = \sum_{j=1}^n [(T_{to_mod(j)} - T_{to_measured(j)})^2 + (T_{so_mod(j)} - T_{so_measured(j)})^2] \quad (2.4)$$

The suggested method was validated using operation records of an industrial shell and tube heat exchangers paired with a crude distillation unit.

A nonlinear observer-based on the Lyapunov theorem is proposed by Delrot et al.[15] for fouling detection, as shown in figure 2.1 , where a simplified distributed model is used to construct the heat exchanger nonlinear state-space model. Real experimental data used for model validation.

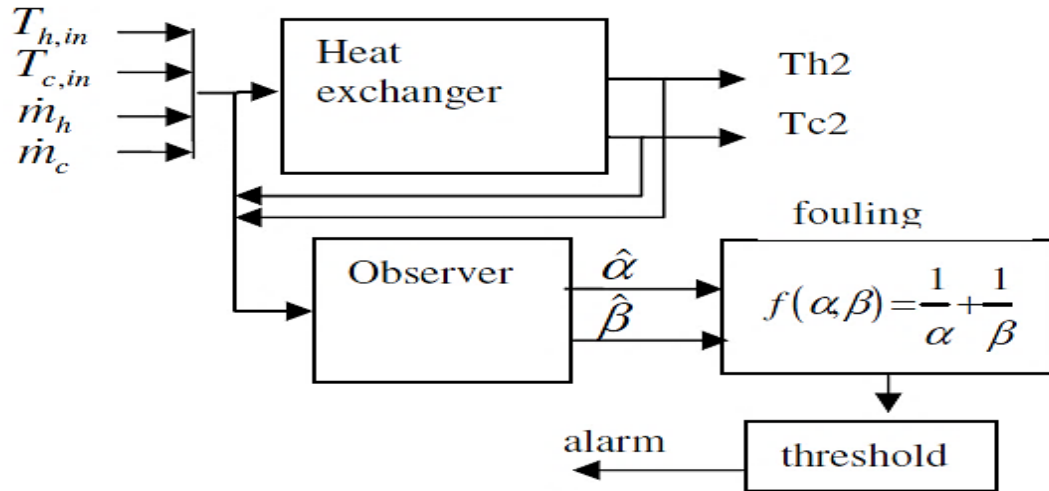


Figure 2. 1: Nonlinear observer

An extended Kalman filter is suggested by Jonsson et al. [16] for fouling detection, where a lumped nonlinear state-space model utilized to model a counter flow plate heat

exchanger. A CFD software used for system simulation considering mass flow rates, outlet temperatures, and inlet temperatures as the system's measurements.

Sabrina Delrot et al.[17] presented a Takagi-Sugeno observer for fouling detection in a counter flow tabular heat exchanger where the fuzzy observer is designed according to the physical model obtained by dividing the heat exchanger into multiple sections and finding the lumped model for each section. ANSYS fluent used for model simulation where fouling has been simulated by changing the thermal conductivity of the inner tube. The developed observer showed good sensitivity toward fouling detection and does not impose that the system should be in a steady state.

Sun, Saqi, and Xie [18] proposed a model that predicts fouling resistance based on a relevance vector machine with a wavelet kernel where the model is trained using experimental data.

A semiempirical model adopted for fouling detection in [19] by Dragan, where a linear model with unknown parameters is derived from the first principles, then least squared method (LSM) deployed for estimation of unknowns. The same author in [20] compared different detection techniques, including Kalman filter, extended Kalman filter, NTU, fuzzy observers, and ANN applied for cross flow and counter flow heat exchangers.

A lock-in semi-empirical technique for fouling detection is proposed by Andrjesdóttir et al. [21]. The technique was based on the lock-in amplifier channels theory, which is used for noise attenuation in signal processing applications. Based on plate and frame heat exchanger a numerical model is developed, and an experimental data has been used for validation where the obtained results showed that the proposed technique has a high

sensitivity in addition to its ability to differentiate between the effect of a decrease in mass flow rate and fouling effect. Lalot et al. [22] applied this technique numerically by injecting a small perturbation in the inlet temperature of the side where the fouling is expected to occur using an electrical heater, as shown in Figure 2.2 where the temperature changes in a periodical manner. Considering the parallel flow plate and frame heat exchanger as a case study, the obtained results illustrated that a window of four million samples is appropriate for accurate fouling detection.

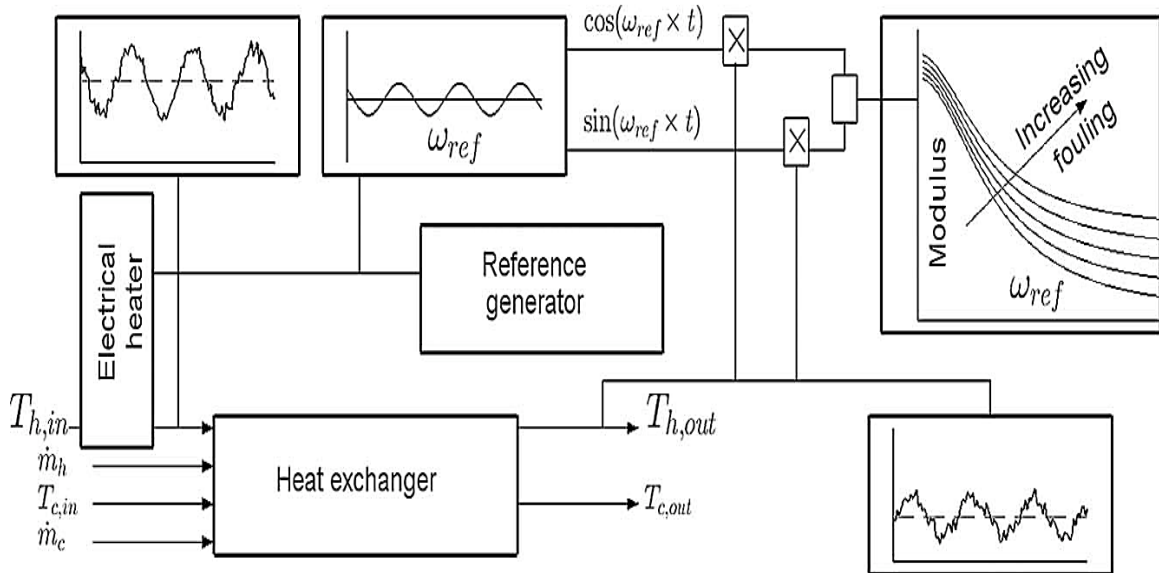


Figure 2. 2: Implementation of a lock-in technique[22].

A distributed dynamic semiempirical model is proposed by Coletti and MacChietto [23] for a tube-side fouling prediction taking into account the change in fluid properties due to temperature, heat exchanger geometric parameters, and variation in fouling accumulation with time where the model can capture the spatial and temporal variation of the system's

states. The model was validated with a practical dataset taken from a crude oil refinery where the model showed an error of less than 2% for one year ahead prediction.

Al Hadad, Schick, and Maillet [24] proposed a detection technique based on the variation of the heat exchanger thermal impulse responses where the system impulse response is firstly identified at the clean state and then under operation assuming that the model is time-invariant, linear, and under steady-state operation. Shell and tube heat exchanger model simulated using COMSOL software where the impulse response is identified by injecting a thermal disturbance in the hot side of the heat exchanger through a surface heat source and then measuring the responses of outlet temperatures where the results showed that this method is sensitive for change in fouling.

Radhakrishnan et al. [25] proposed an ANN model to predict outlet temperatures of shell and tube heat exchanger. ANN is trained based on a historical plant data using feedforward and recurrent Neural network architectures where the latter showed a better prediction accuracy. Forty-four features considered initially for model developing and then reduced to 25 features using principal component analysis (PCA) and partial least squares (PLS) techniques. The cleaning process can be scheduled according to the decrement in the efficiency of heat transfer based on predicted values of temperatures. Still, the developed model showed a poor generalization capability.

Based on experimental datasets gathered from literature, Davoudi and Valeri [26] developed an ANN fouling prediction model using a shallow neural network with ten hidden neurons where fluids properties and time are considered as input to ANN while fouling factor was the output. The model showed a small prediction error with $MSE=0.0013$.

A fouling detection method based on Elman NN depicted in figure 2.3 is proposed by Wang et al. [27]. The weights of the NN have been optimized by genetic algorithm. An experiment is conducted to simulate the formation of calcium carbonate ($CaCO_3$) fouling in a shell and tube heat exchanger where a self-designed setup captures the experimental data of fouling resistance, pH, and dissolved oxygen used for NN training. The detection method showed a total error of 8.78%.

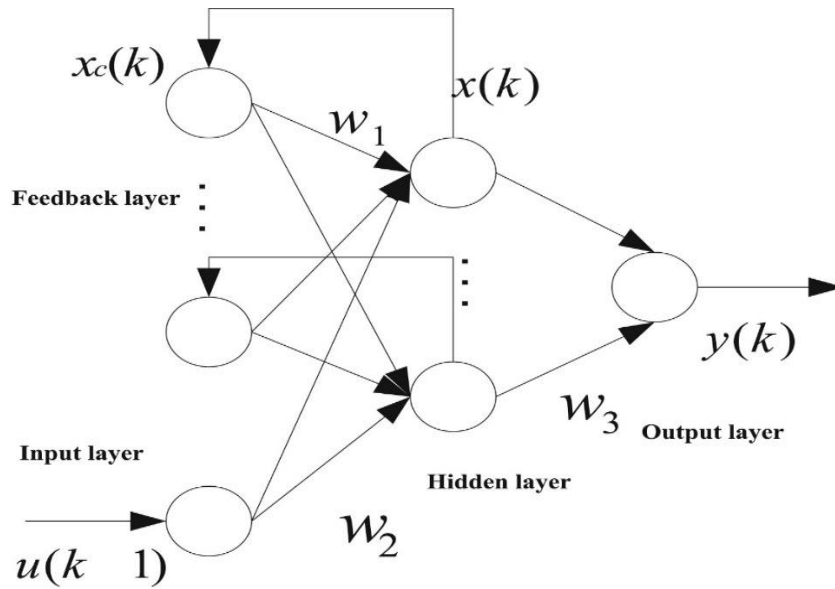


Figure 2. 3: Elman neural network architecture[27]

2.2 Fouling Compensation

Fouling leads to deterioration in the effectiveness of heat transfer and subsequently affects the system dynamics. According to [28], about 80% of heat exchangers control systems in industry are based on PID controllers that are manually tuned. Trafczynski et al. [28] investigated the influence of fouling on the dynamic of PID controlled shell and tube heat exchangers where heat exchanger is divided into cells array. Then a linearized lumped

model is derived. A real data is used to validate the model, then based on the developed model, MATLAB used to simulate two series-connected heat exchangers and the PID-controller as depicted in figure 2.4 under different fouling conditions. The results showed that with an increase in fouling resistance, the controller parameters need to be retuned periodically.

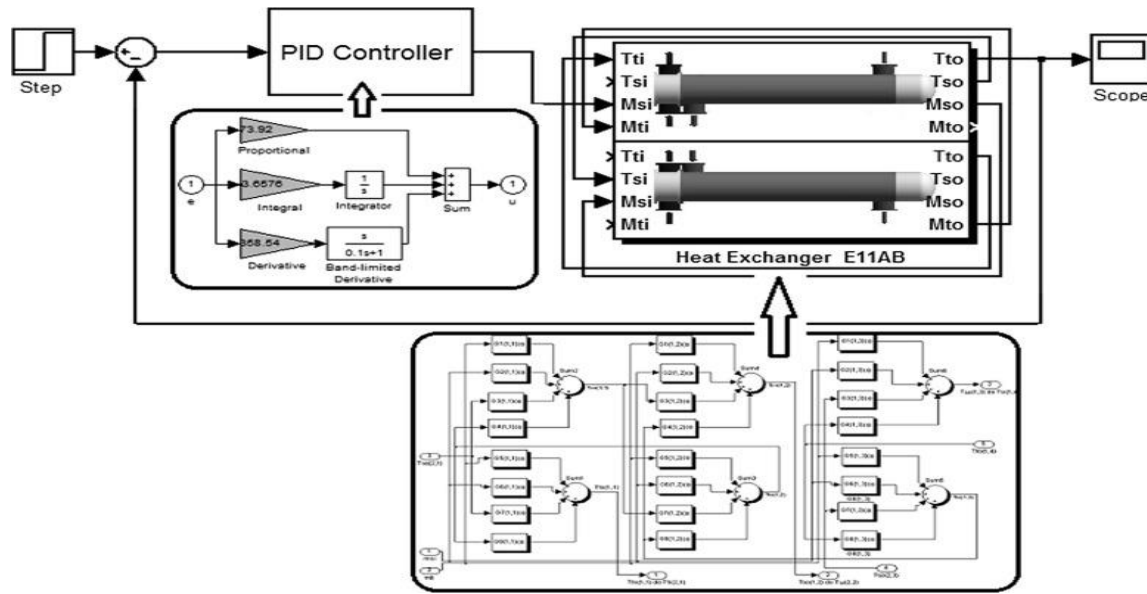


Figure 2. 4: Simulink model of the heat exchangers and PID controller[28].

Based on a similar model, de Carolina et al. [29] presented two strategies for tuning a PID controller for shell and tube heat exchangers (STHXs) undergoing fouling. MATLAB/SIMULINK utilized to simulate the controlled system by applying a step input in the shell flow rate. The system has been examined for three case studies with different operating conditions and fluids. For each case, various fouling resistances have been considered where PID is retuned for these fouling resistances using two tuning strategies. The first strategy is based on a built-in SIMULINK PID tuner. In contrast, the second one

is based on sequential quadratic programming (SQP) algorithm, and it has been reported that the latter strategy has a better performance.

Oravec et al. [30], designed a robust model predictive controller (MPC) for industrial shell and tube heat exchangers. The influence of fouling is modeled as a parametric uncertainty. Based on the cells array approach, the STHX has been modeled by a lumped model, and then a discrete-time state-space model is derived. Firstly, a robust MPC controller is designed to control the model. Then an integral action is added to the controller, which helps in removing steady state error. The optimization problem is formulated as a convex optimization problem. Figure 2.5 shows the proposed control architecture. Four STHX units were considered, with four fouling levels and for each unit shell-side flow rate regarded as the manipulated variable. The designed controller compared with The PID controller and the attained results from MATLAB/SIMULINK showed that the proposed controller almost outperforms the PID controller in terms of disturbance rejection, reference tracking, and energy saving.

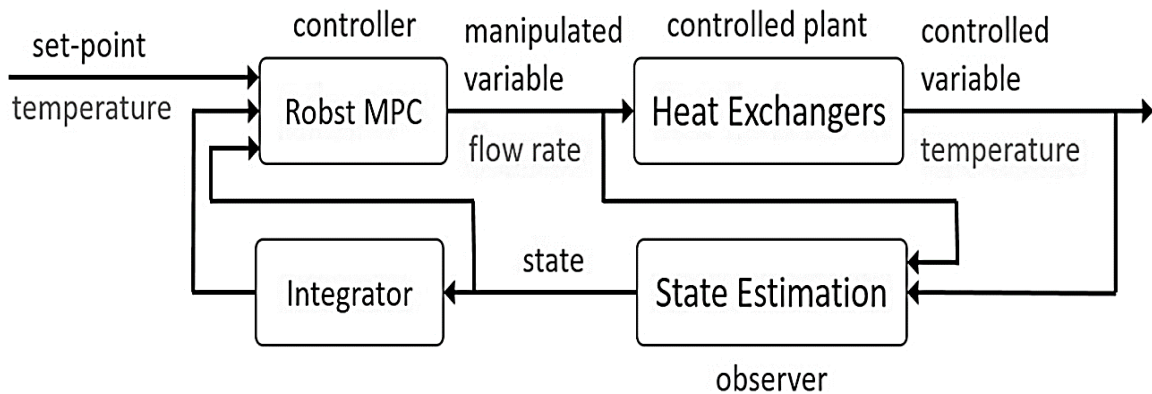


Figure 2. 5 : Robust MPC with integral action control architecture[30].

In an extended study Trafczynski et al.[31] investigated the fouling influence on PID controlled heat exchanger networks (HEN) shown in figure 2.6. MATLAB\SIMULINK

used for system simulation where the authors concluded that with the increase of heat exchanger units in the PID controlled HEN, the fouling influence on the dynamic behavior becomes weak or negligible.

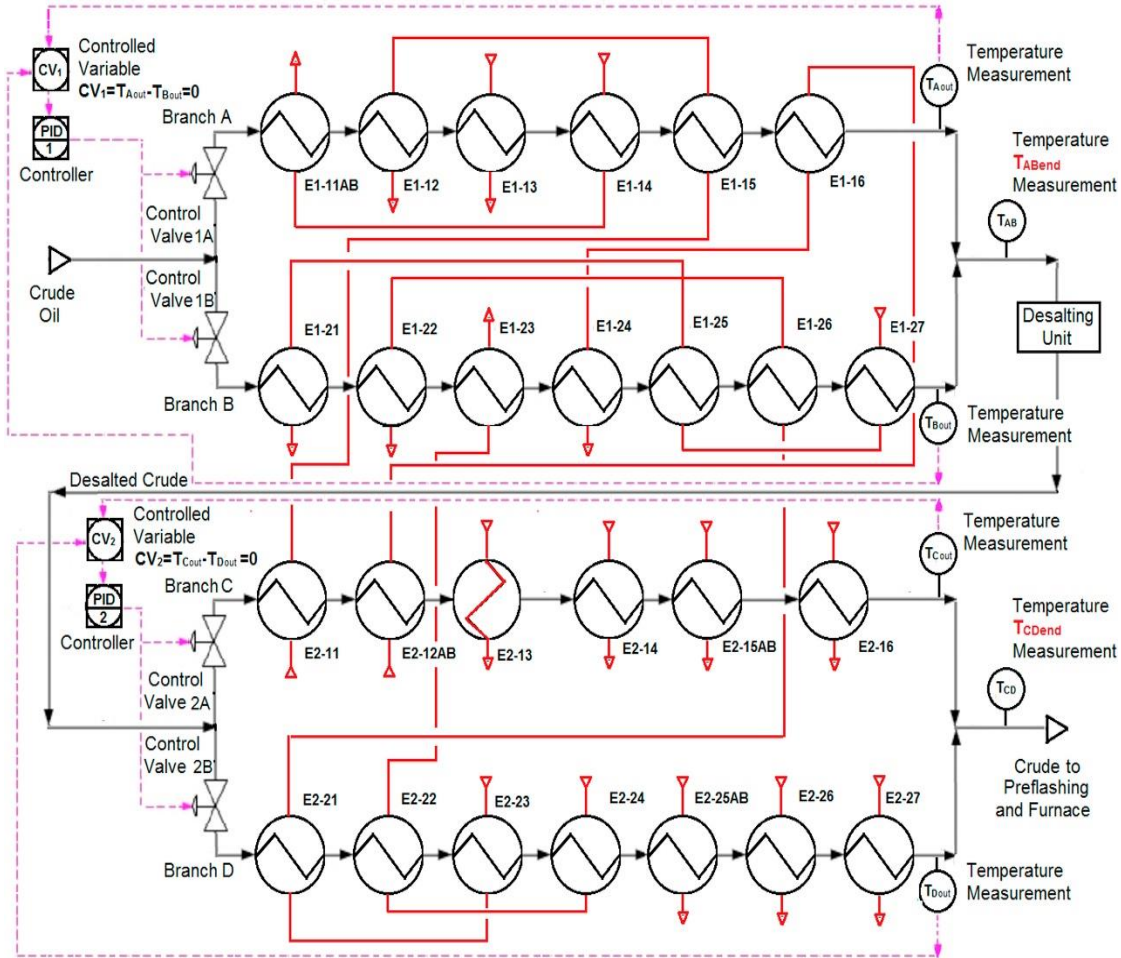


Figure 2. 6: PID controlled HEN scheme[31].

Trafczynski et al.[32] proposed a simple strategy to tune PID controlled HEN shown in figure 2.6 that only requires measurements of HEN parallel branches' outlet temperatures where the suggested approach ensures that their values are equal. The proposed strategy achieved 0.75 MW heat recovery, which represents about a 1.5 % increase in total heat recovery.

CHAPTER 3

Double Pipe Heat Exchanger Modelling

3.1 Introduction

The double pipe heat exchanger (DPHE) represents one of the standard heat exchangers that is widely known for its simplicity and applicability. This type of heat exchangers is broadly utilized in food, oil and gas, and chemical industries. It is also of great significance when a wide temperature gradient is needed. Moreover, DPHE has high popularity in many small industries owing to its low design and maintenance costs [33]. The DPHE dynamic model is developed based on one-dimensional finite-difference analysis of both parallel flow type and counter flow type of the double pipe heat exchanger shown in Figure 3.1 and Figure 3.2, subsequently. Figure 3.3 depicts the cross-section view of DPHE.

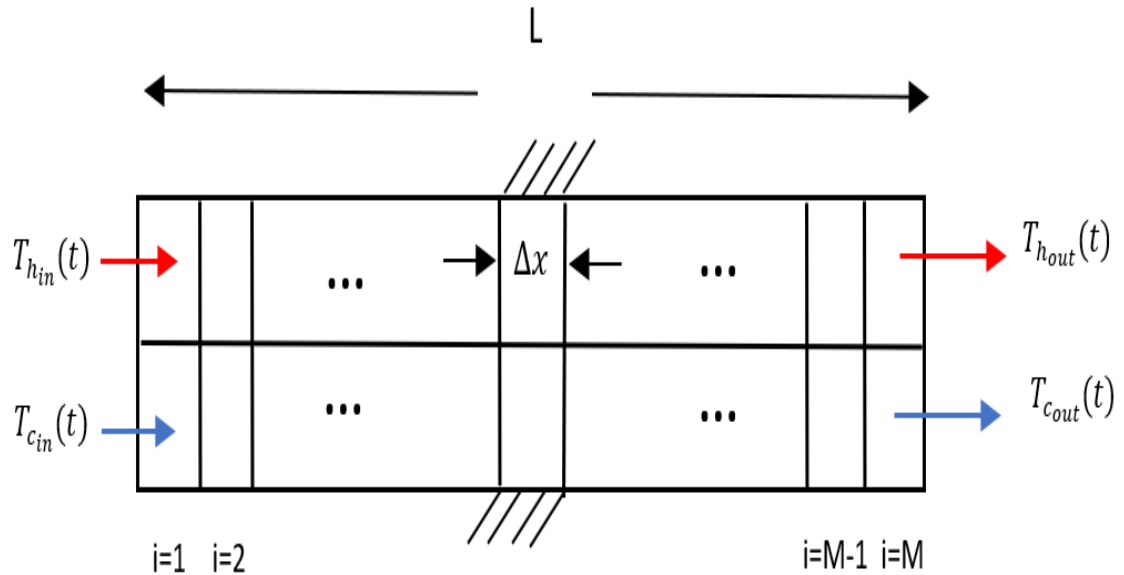


Figure 3. 1: Parallel flow heat exchanger

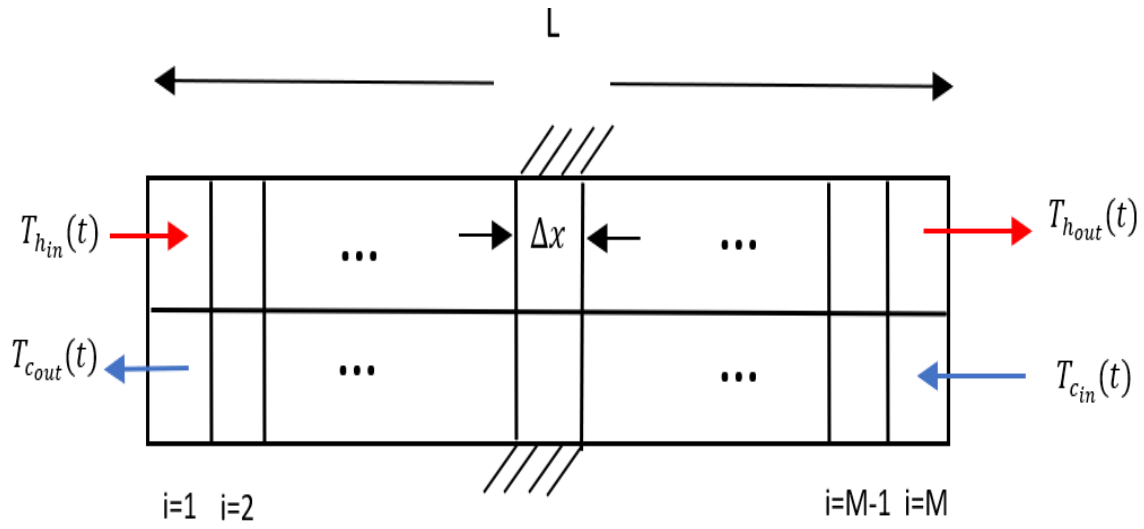


Figure 3. 2: Counter flow heat exchanger

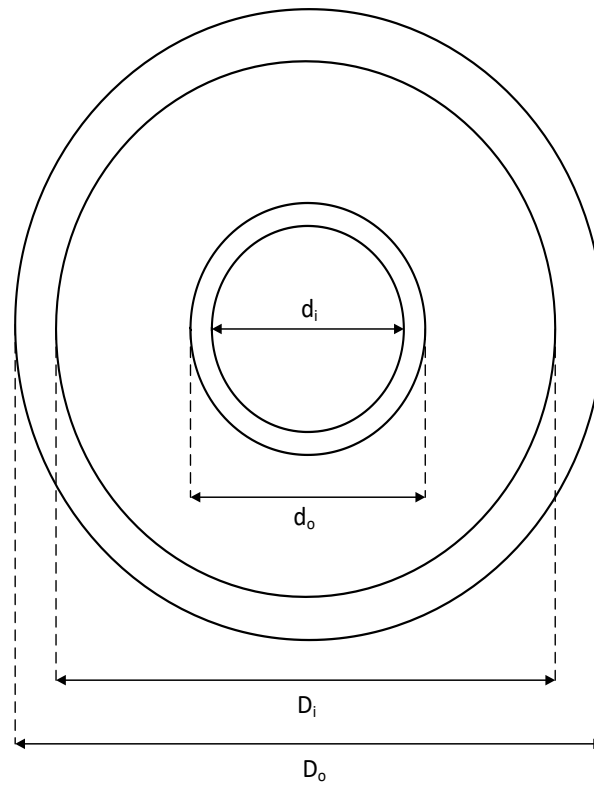


Figure 3. 3: Cross-section view of the double pipe heat exchanger

Where

$T_{hin(t)}$ is the hot side inlet temperature.

$T_{h_{out}(t)}$ is the hot side outlet temperature.

$T_{c_{in}(t)}$ is the cold side inlet temperature.

$T_{c_{out}(t)}$ is the cold side outlet temperature.

L is the length of pipe.

M is the number of segments.

Δx is the length of each partition.

i is a spatial index.

3.2 Thermal Dynamic Model of The Double Pipe Heat Exchanger

The following assumptions were used for the model derivation:

- 1- The heat transfer coefficient is uniform along the pipe length.
- 2- The rate of change in wall temperature is neglected.
- 3- The density and heat capacity of hot and cold fluids are constants.
- 4- The hot and cold fluids are both in liquid phase.

According to the first law of thermodynamic (conservation of energy)[34]

$$\dot{E}_{in} - \dot{E}_{out} = \dot{E}_{st} = \rho C_p V \frac{\partial T}{\partial t} \quad (3.1)$$

Where

$\dot{E}_{in}$ and $\dot{E}_{out}$ denote the energy transfer rate into and out of the heat exchanger, respectively. Whereas the rate of change in the system's stored energy is represented by $\dot{E}_{st}$.

Assuming that the hot fluid flows through the inner pipe and the cold fluid flows through the outer pipe of the heat exchanger, Equation (3.1) can be rewritten as follows

$$\rho_h C_{P_h} \Delta V_1 \frac{\partial T_h(t,i)}{\partial t} = \dot{m}_h C_{P_h} (T_h(i-1, t) - T_h(i, t)) - U(t) \Delta A_s(i) (T_h(i, t) - T_c(i, t)) \quad (3.2)$$

$$\rho_c C_{P_c} \Delta V_2 \frac{\partial T_c(t,i)}{\partial t} = \dot{m}_c C_{P_c} (T_c(i-1, t) - T_c(i, t)) + U(t) \Delta A_s(i) (T_h(i, t) - T_c(i, t)) \quad (3.3)$$

Where

$\dot{m}_h$ = hot fluid mass flow rate (Kg/sec).

ρ_h = hot fluid density (Kg/m³).

$\dot{m}_c$ = cold fluid mass flow rate (Kg/sec).

ρ_c = cold fluid density (Kg/m³).

C_{P_h} = Specific heat at a constant pressure of the hot fluid.

C_{P_c} = Specific heat at a constant pressure of the cold fluid.

$U(t)$ = Overall heat transfer coefficient (W/m².K).

ΔA_s = The change in the surface area (m²).

ΔV_1 = The change in the inner pipe volume (m³).

Δt = Time step (sec).

ΔV_2 = The change in the outer pipe volume (m³).

By using explicit discretization, we obtain

$$\frac{T_h(i,t+\Delta t)-T_h(i,t)}{\Delta t} = \frac{(\dot{m}_h C_{P_h}(T_h(i-1,t)-T_h(i,t))-U(t)\Delta A_s(i)(T_h(i,t)-T_c(i,t)))}{\rho_h C_{P_h} \Delta V_1} \quad (3.4)$$

$$\frac{T_c(i,t+\Delta t)-T_c(i,t)}{\Delta t} = \frac{(\dot{m}_c C_{P_c}(T_c(i-1,t)-T_c(i,t))+U(t)\Delta A_s(i)(T_h(i,t)-T_c(i,t)))}{\rho_v C_{P_v} \Delta V_2} \quad (3.5)$$

After some arrangements Equations (3.4) and (3.5) can be written as follows

$$T_h(i, t + \Delta t) = T_h(i, t) + \frac{\Delta t (\dot{m}_h C_{P_h}(T_h(i-1,t)-T_h(i,t))-U(t)\Delta A_s(i)(T_h(i,t)-T_c(i,t)))}{\rho_h C_{P_h} \Delta V_1} \quad (3.6)$$

$$T_c(i, t + \Delta t) = T_c(i, t) + \frac{\Delta t (\dot{m}_c C_{P_c}(T_c(i-1,t)-T_c(i,t))+U(t)\Delta A_s(i)(T_h(i,t)-T_c(i,t)))}{\rho_c C_{P_c} \Delta V_2} \quad (3.7)$$

Where

$$\Delta A_s = \pi d_o \Delta x$$

$$\Delta V_1 = \frac{\pi d_o^2}{4} \Delta x$$

$$\Delta V_2 = \frac{\pi D_i^2}{4} \Delta x \quad (3.8)$$

3.3 Double Pipe Heat Exchanger Inner Pipe Pressure Drop

The pressure drop in heat exchanger inner pipe is given by[35]

$$\Delta P = \frac{\rho_1 U_{mi}^2 f L}{d_{ia}} \quad (3.9)$$

Where

U_{mi} = dynamic velocity of the inner fluid.

d_{ia} = the actual inner diameter of the inner pipe.

f = Darcy friction factor.

The dynamic velocity depends on the density and mass flow rate of the inner fluid as well as the inner diameter as revealed below

$$U_{mi} = \frac{\dot{m}_h}{0.25\rho_1\pi d_{ia}^2} \quad (3.10)$$

The Reynolds number Re for the inner pipe, fluid is calculated as follows

$$Re = \frac{\rho_h U_{mi} d_{ia}}{\mu} \quad (3.11)$$

Where μ represents the dynamic viscosity of the inner fluid. The friction factor f for laminar flow regime ($Re \leq 2000$) is given by

$$f = \frac{64}{Re} \quad (3.12)$$

While in case of the turbulent flow ($4000 < Re < 10^8$) f is given by[36]

$$f = \frac{0.25}{\left(\log_{10}\left(\frac{k_s}{3.7D} + \frac{5.74}{Re^{0.9}}\right)\right)^2} \quad (3.13)$$

Where k_s denotes the roughness of the fluid inner surface.

In case of transition flow ($2000 < Re \leq 4000$) f can be formulated as

$$f = C_{tr} \left(\frac{64}{2000}\right) + (1 - C_{tr}) \left(\frac{0.25}{\left(\log_{10}\left(\frac{k_s}{3.7D} + \frac{5.74}{4000^{0.9}}\right)\right)^2}\right) \quad (3.14)$$

Where

$$C_{tr} = 2 - \left(\frac{Re}{2000}\right) \quad (3.15)$$

3.4 Fouling Effect

The fouling has been considered for the inner pipe only while the outer pipe fouling is neglected. As mentioned earlier, fouling affects both the heat transfer coefficient and pressure drop. For the fouled heat exchanger heat transfer coefficient can be evaluated as follows

$$U_f(t) = \frac{U_c}{1 + U_c R_f} \quad (3.16)$$

Where

U_f = heat transfer coefficient under fouling conditions.

U_c = heat transfer coefficient at clean state.

R_f = fouling resistance.

The actual inner pipe diameter in case of inner pipe fouling is given by

$$d_{ia} = d_i - 2 * R_f * K_f \quad (3.17)$$

Where k_f represents the thermal conductivity of fouling material.

3.5 Numerical Simulation

Based on the previous equations, the system has been modeled in MATLAB according to the parameters shown in table 3.1. Both parallel flow and counter flow DPHE arrangements have been numerically simulated also the thermal and hydraulic effects of fouling build-up are investigated through simulation. The hot and cold fluids are water-water in the liquid state.

Table 3. 1: Heat Exchanger Parameters

Hot fluid mass flow rate ($\dot{m}_h$)	0.2 Kg/sec
Cold fluid mass flow rate ($\dot{m}_c$)	0.1 Kg/sec
Specific heat at a constant pressure of hot fluid (C_{ph})	4180 J/Kg.K
Specific heat at a constant pressure of cold fluid (C_{pc})	4180 J/Kg.K
Hot fluid density (ρ_h)	1000 Kg/m ³
Cold fluid density (ρ_c)	1000 Kg/m ³
Length of pipe	5 m
Overall heat coefficient (U)	1000 W/m ² .K
Number of segments (M)	50
Time step	0.01 sec
Hot side inlet temperature	100°C
Cold side inlet temperature	20°C
Inner diameter of the inner pipe (d_i)	0.04m
Outer diameter of the inner pipe (d_o)	0.05m
Inner diameter of the outer pipe (D_i)	0.1m
Roughness of fluid inner surface (k_s)	0.001 m
Thermal conductivity of fouling material	0.1 W/m.K

For parallel flow DPHE, the dynamic outlet temperatures are illustrated in figure 3.4, while figure 3.5 displays the inner pipe pressure drop. Figure 3.6 shows the temperature gradient at different simulation times, and figure 3.7 depicts the steady-state temperature gradient. The simulation time is adjusted to one hour, where the DPHE reaches the steady-state at 0.1 hours (360 seconds) approximately where the steady state outlet temperatures are 75.0520°C and 69.8959°C for hot and cold fluid, respectively. The analytical steady state solution using effectiveness ratio method [37] gives 74.9253°C and 70.1493°C for the outlet temperature of hot and cold fluid, respectively .

In the case of the counter flow DPHE arrangement, the dynamic outlet temperatures are depicted in figure 3.8. Figure 3.9 shows the inner pipe pressure drop. Figure 3.10 illustrates the temperature gradient at different simulation times, while figure 3.11 reveals the steady-state temperature gradient. In this case, the DPHE takes about 0.15 hours (540 minutes) to reach the steady-state. In light of these figures, the counter flow DPHE configuration allows a high heat transfer rate compared to the parallel flow DPHE. the steady state outlet temperatures are 69.3374°C and 80.2147°C for hot and cold fluid, respectively where the analytical solution gives 69.715°C and 80.5696°C for the outlet temperature of hot and cold fluid, respectively.

Both Parallel flow and counterflow DPHE dynamic models shows small deviation from the analytical solution of thermal steady state model. Increasing the number of segments can reduce this error but this also increases simulation time. So, selecting the number of segments is a tradeoff between accuracy and simulation time.

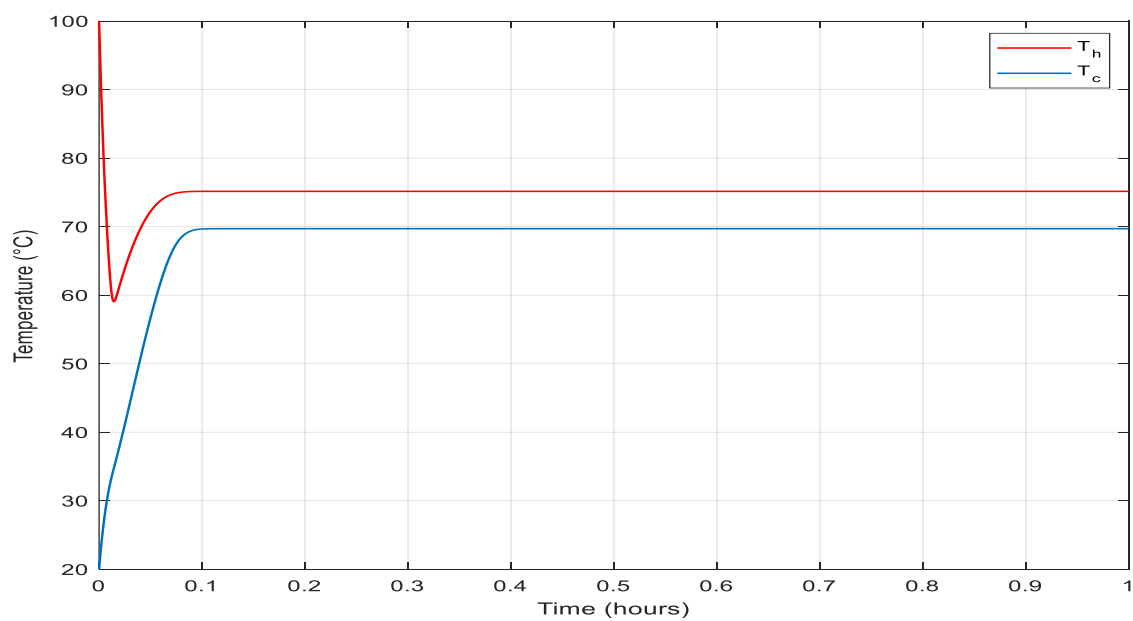


Figure 3. 4: Parallel flow DPHE outlet temperatures

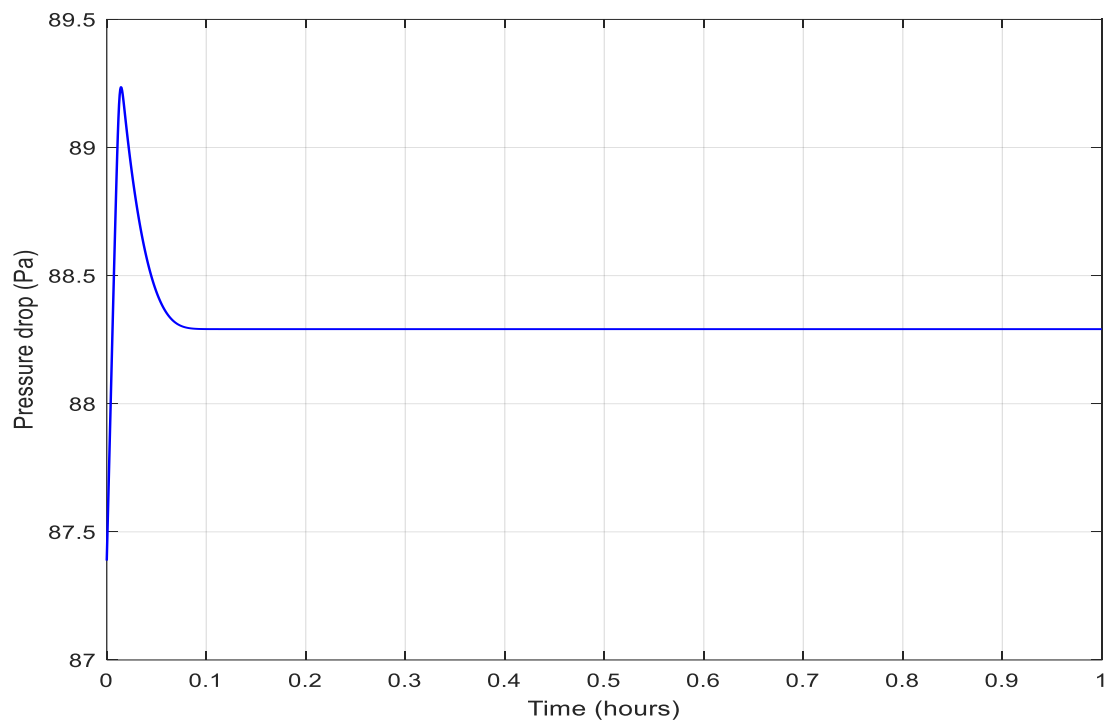


Figure 3. 5: Parallel flow DPHE pressure drop

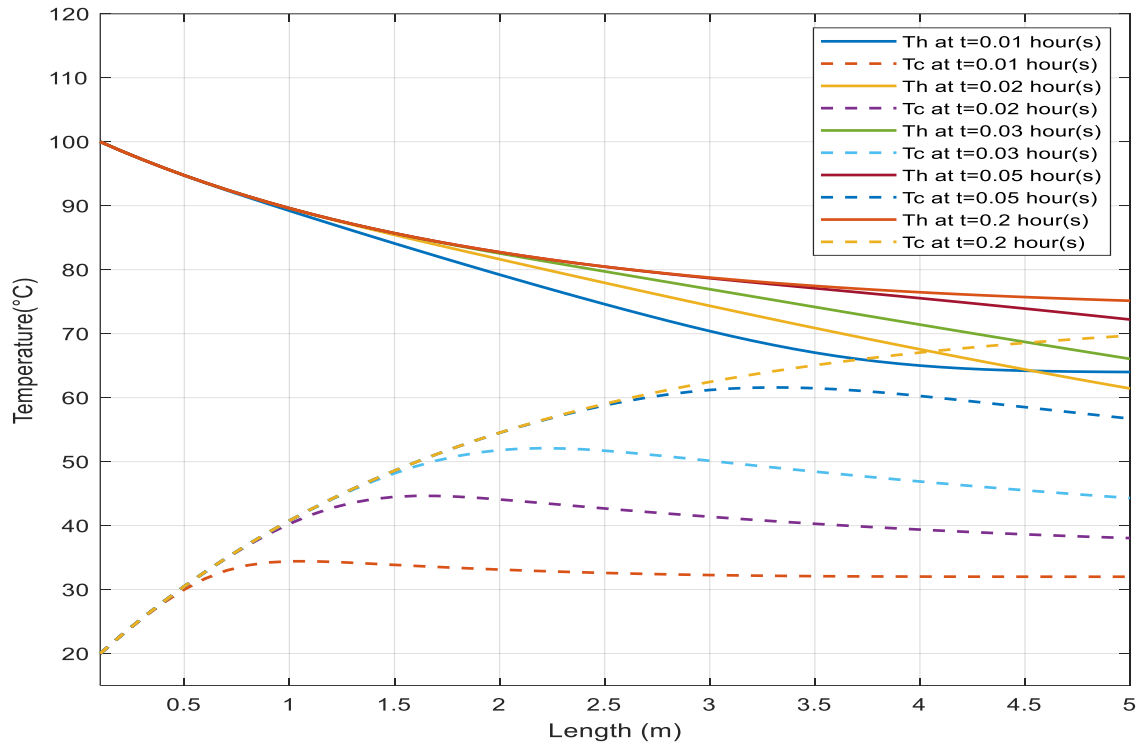


Figure 3. 6 : Parallel flow outlet temperatures gradient at different simulation times

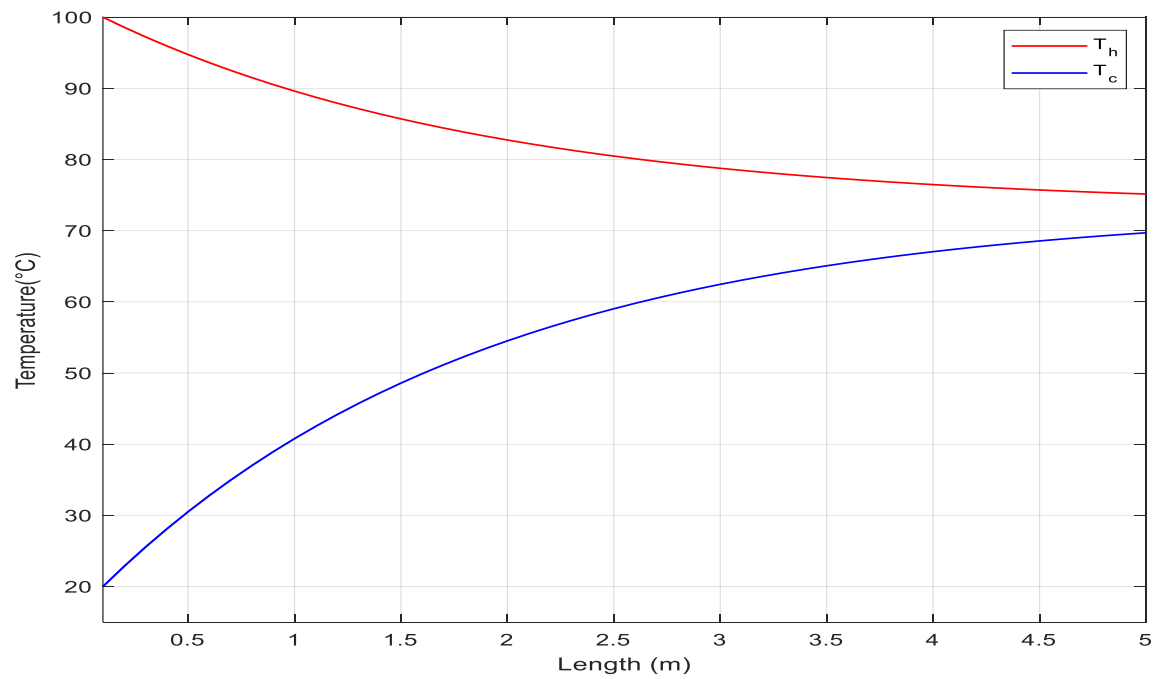


Figure 3. 7: Parallel flow DPHE steady state temperature gradient

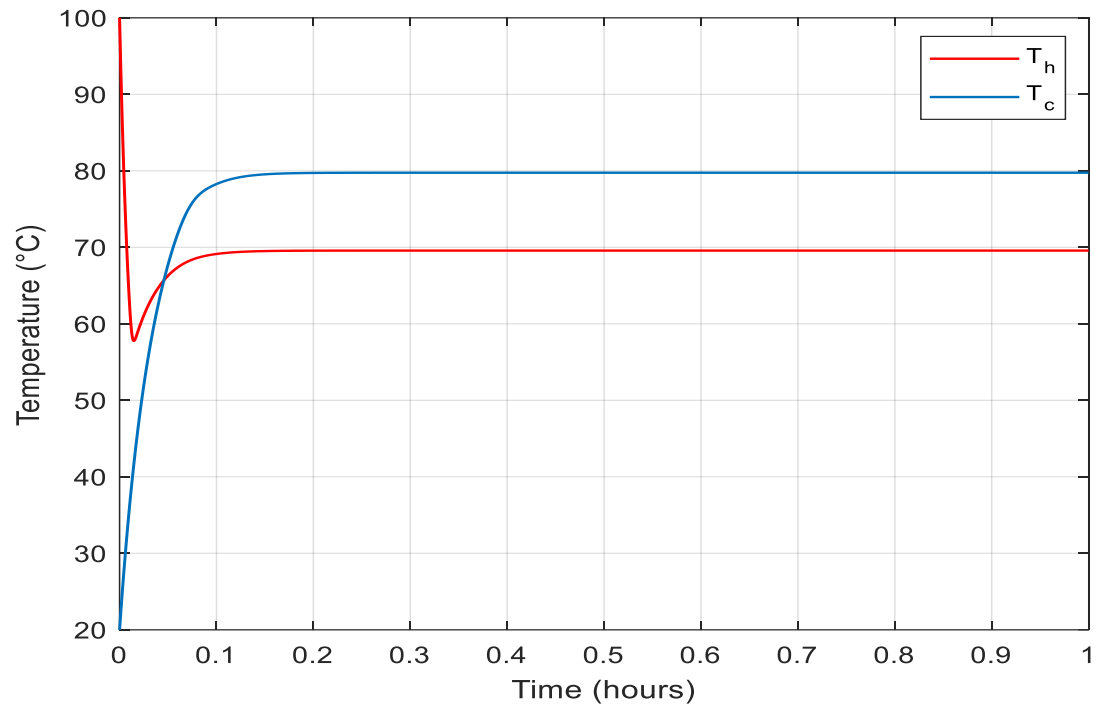


Figure 3. 8: Counter flow DPHE outlet temperatures

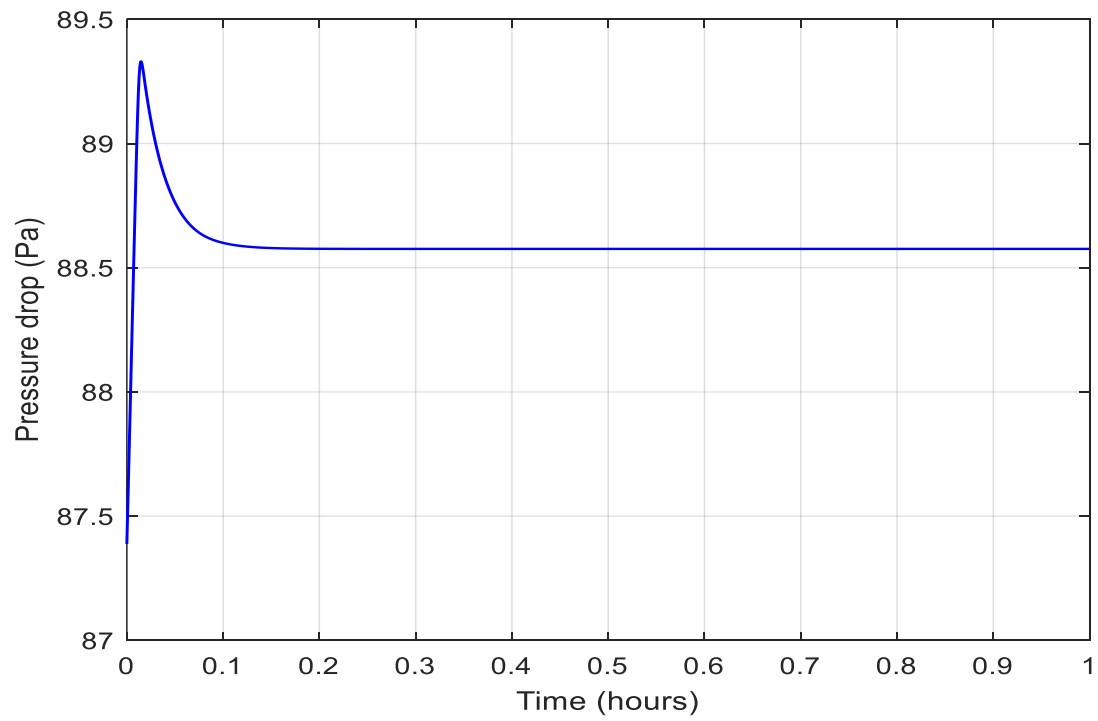


Figure 3. 9: Counter flow DPHE pressure drop

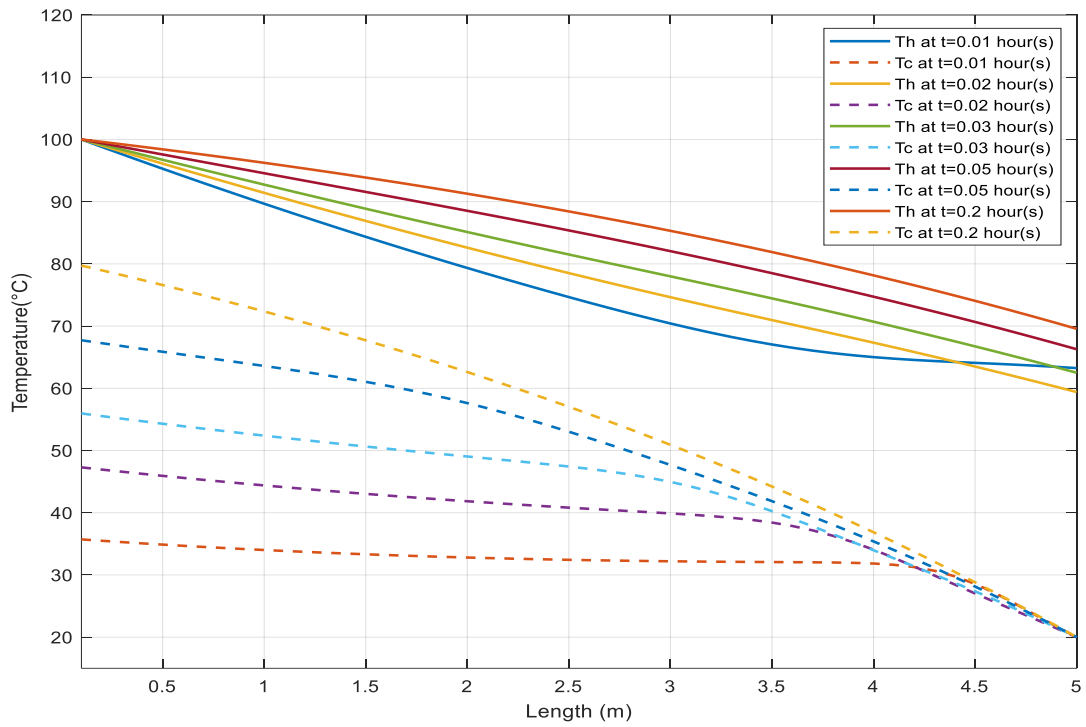


Figure 3. 10: Counter flow DPHE Outlet temperatures gradient at different simulation times

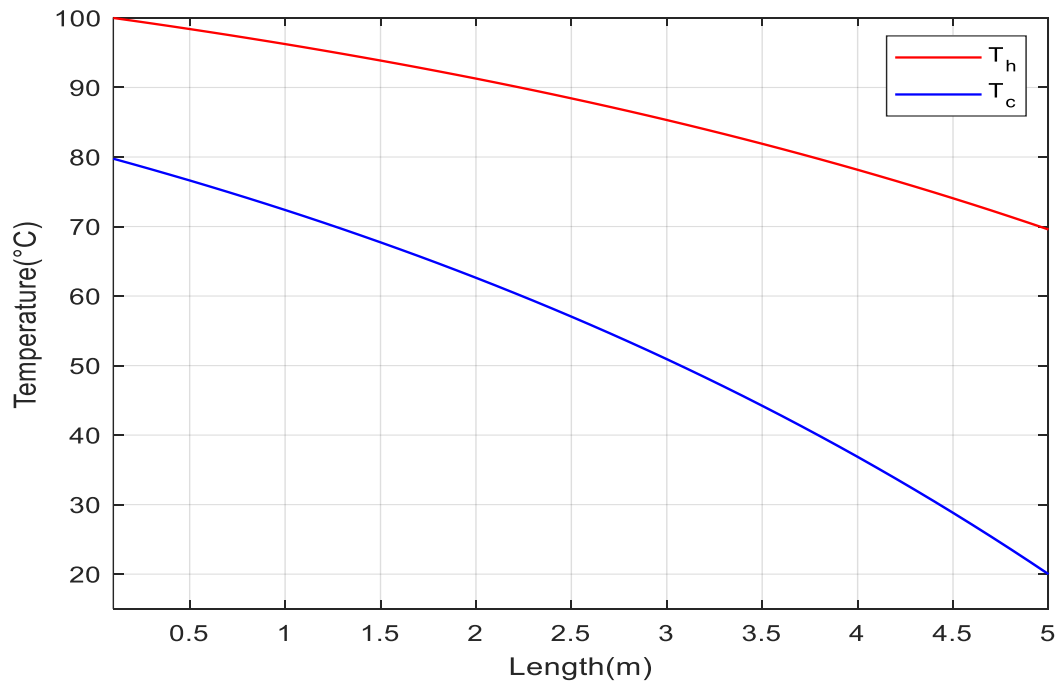


Figure 3. 11: Parallel flow DPHE Steady-state temperature gradient

The fouling resistance has been varied asymptotically, as demonstrated in figure 3.12, to investigate the effect of inner pipe fouling build-up on the DPHE heat exchanger. The outlet temperatures under fouling build-up conditions for both parallel flow and counter flow DPHE arrangements are depicted in figure 3.13 and figure 3.14, respectively. The change in DPHE pressure drop with fouling for parallel flow and counter flow is illustrated in figures 3.15 and 3.16.

The fouling resistance is varied from 0 to 1.08×10^{-3} which produces a gradual decrease in the heat transfer coefficient (U) starting from 1000 until it reaches 480, which represents a reduction in U by 52% at maximum fouling. Based on figures 3.13 to 3.16, It is clear that the increase in fouling results in the heat transfer rate decline as well as an increase in the pressure drop.

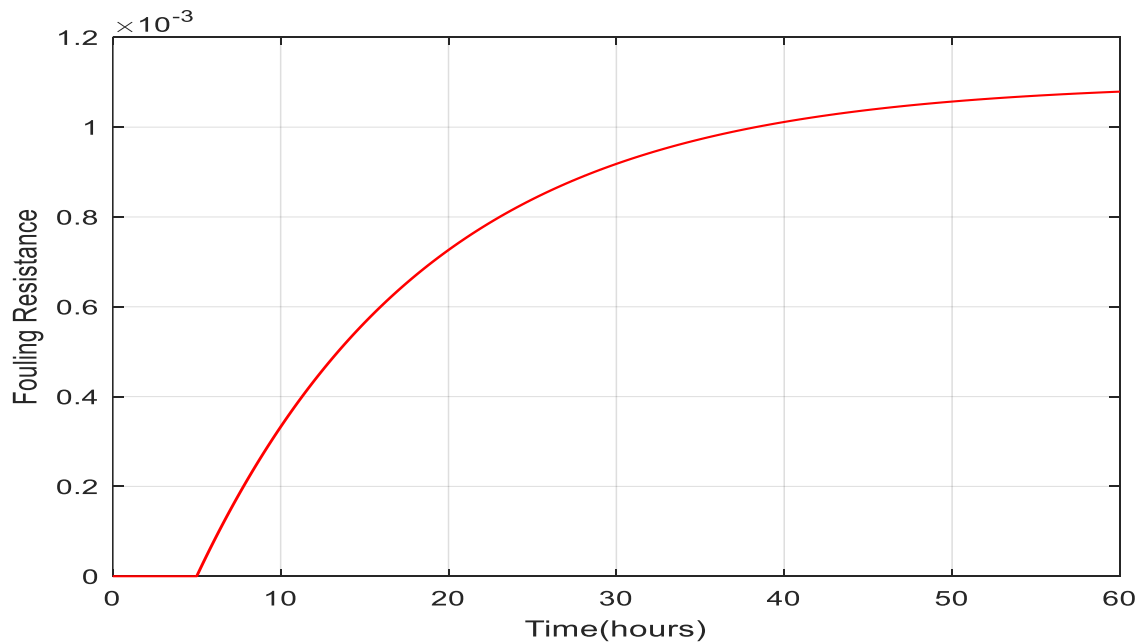


Figure 3. 12: Inner pipe fouling resistance

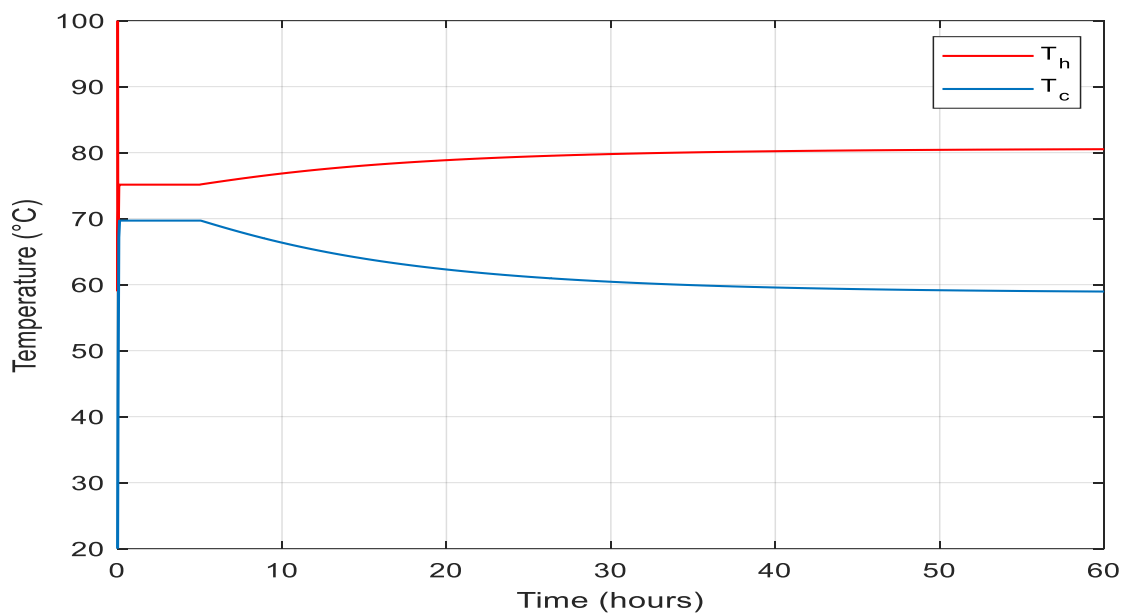


Figure 3. 13: Parallel flow DPHE outlet temperatures under fouling build-up.

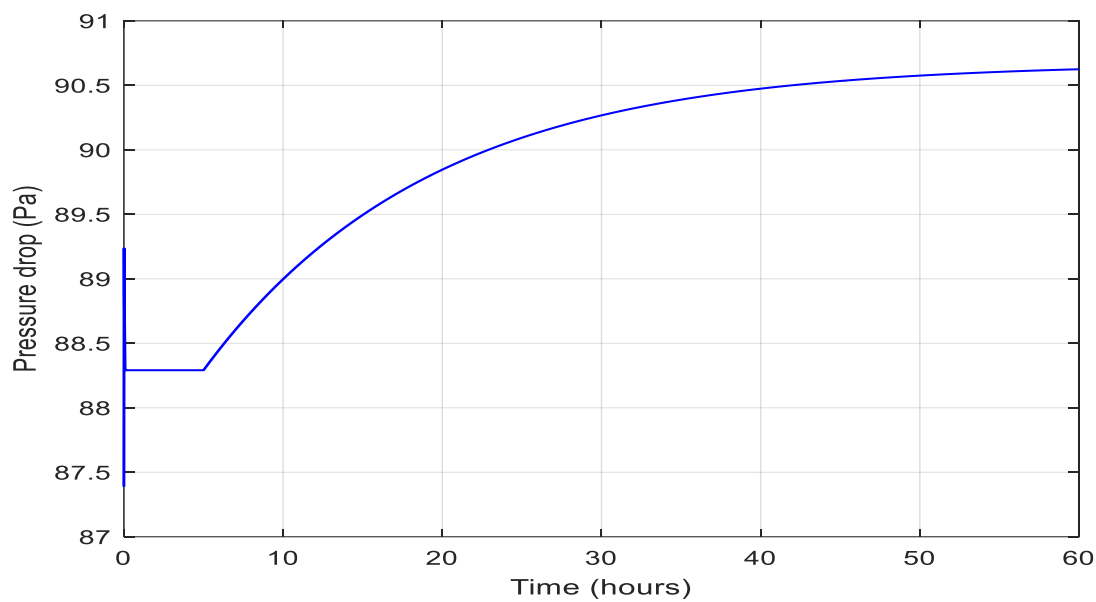


Figure 3. 14: Parallel flow DPHE inner pipe pressure drop under fouling build-up.

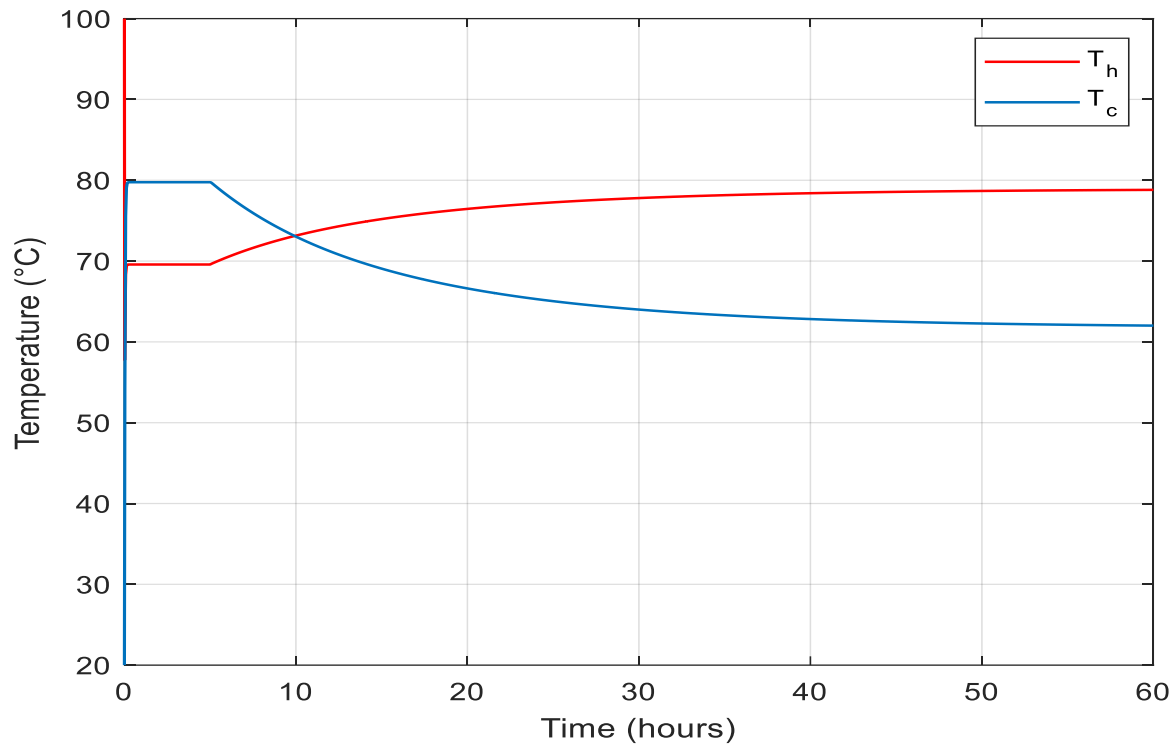


Figure 3. 15: Counter flow DPHE outlet temperatures under fouling build-up.

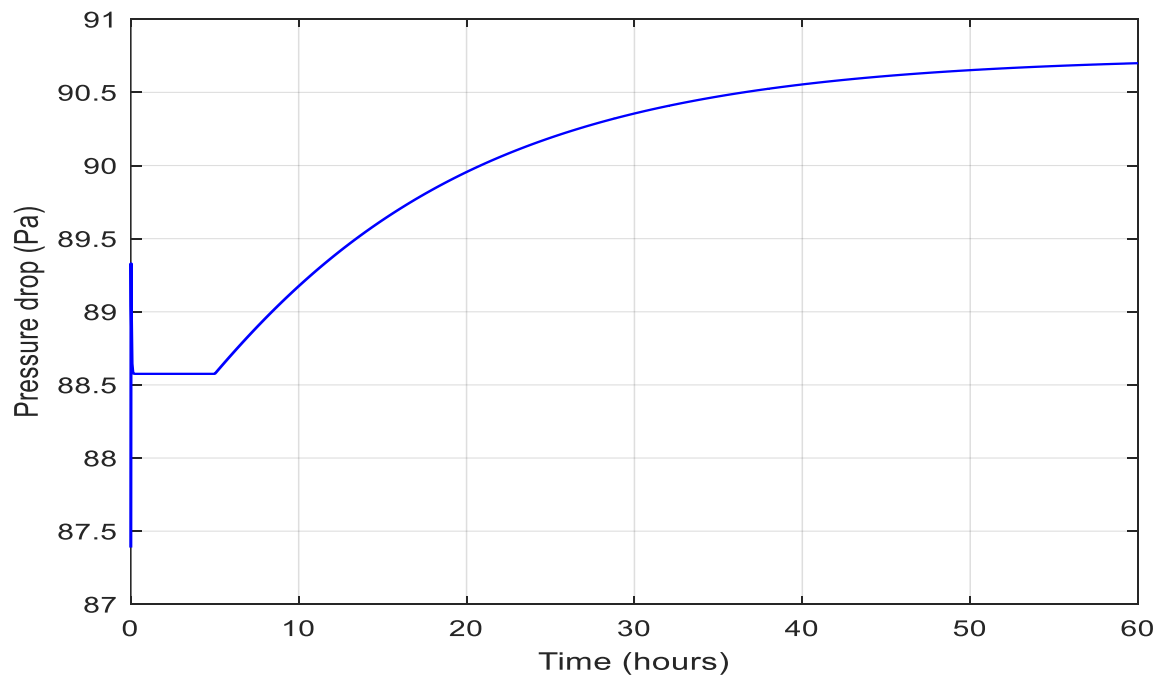


Figure 3. 16: Counter flow DPHE inner pipe pressure drop under fouling build-up.

CHAPTER 4

Heat Exchanger Fouling estimation and prediction

4.1 Introduction

This chapter presents the DPHE inner pipe fouling estimation and prediction based on artificial neural networks. Data-driven models that based on Artificial Neural Networks (ANN) gained a remarkable momentum due to their capability in tackling the complex systems that experience nonlinear patterns such as fouling phenomenon. ANN-based models have been successfully applied to several problems in a diverse range of systems[38]. Two different ANN architectures have been used for estimation and prediction. A feedforward ANN has been employed for fouling estimation based on the DPHE outlet temperatures and the inner pipe pressure drop, while a recurrent neural network, namely long short-term memory (LSTM), has been adopted for prediction purposes.

4.2 Artificial Neural Networks

An ANN is a computational model inspired by the biological neurons in the human nervous system. ANN is one variant of data-driven models, and it is known by its capability to extrapolate complex nonlinear relationships between input sequence and the corresponding output(s). The typical ANN involves three layers: an input layer, a hidden layer, and output layer, as illustrated in figure 4.1, where each layer contains several neurons [39]. Input and output layer dimensions are determined according to the given input and output, whereas the hidden layer dimension depends on the complexity of the required task. Each neuron performs a weighted sum operation on its inputs and throws

this summation through a differentiable activation function, which can be either a linear or a nonlinear function. The neuron's output is given by

$$h = f(W^T X + b) \quad (4.1)$$

where

h is the neuron's output, X is the neuron's input vector and W represents the weight vector. b is a constant represents the neuron's bias, and f is the activation function [40].

The ANN complexity is proportional to the number of neurons in the hidden layer besides the number of hidden layers. If there is more than one hidden layer in ANN architecture, then it called a deep neural network.

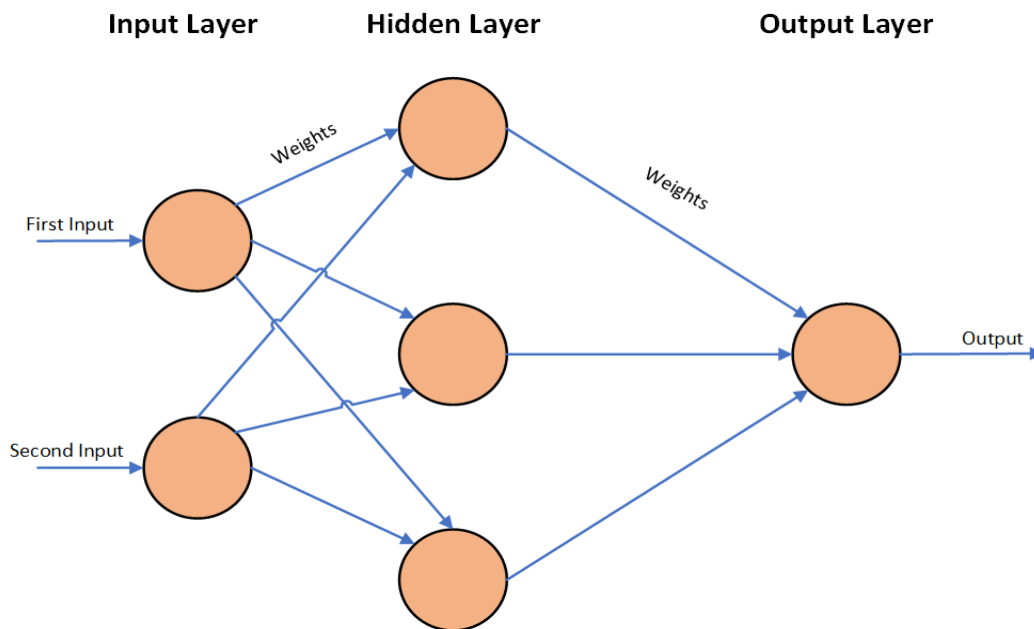


Figure 4. 1:ANN underlying architecture

Typically, given the input and the target output as in classification or regression problems, the ANN training process is performed using gradient decent or one of its variants as an

optimization algorithm. At the same time, the weight update is accomplished via a backpropagation algorithm based on a pre-defined objective function. ANN has several hyper-parameters that affect the training performance, such as the number of hidden layers, the number of hidden neurons, learning rate, and activation function [41]. The employed ANN architecture is depicted in figure 4.2, where a feedforward neural network with 20 hidden neurons is implemented in MATLAB to estimate the fouling resistance.

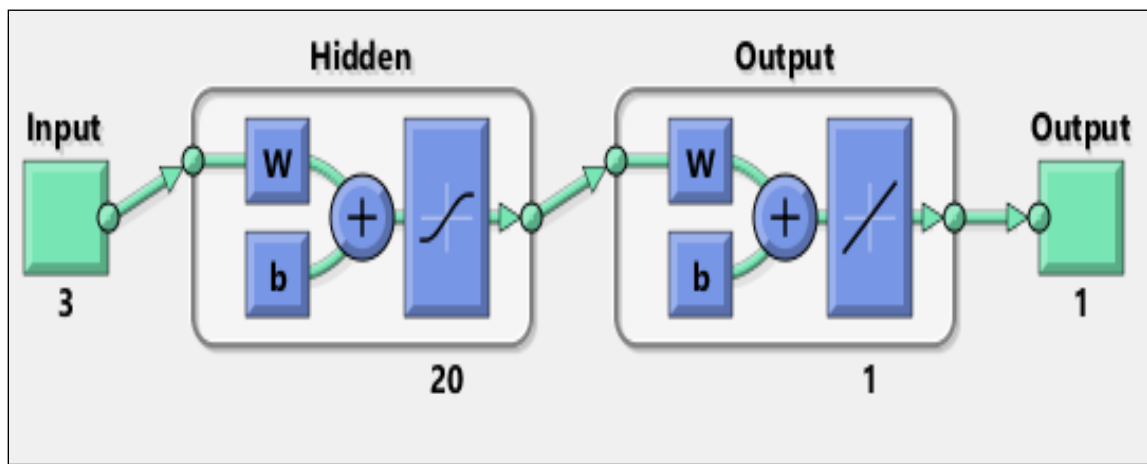


Figure 4. 2: ANN estimation model

4.3 Long Short-Term Memory (LSTM)

Conventional neural networks are independent of previous state values so that it cannot be used for prediction purposes. Recurrent Neural Networks (RNN) were developed to handle dynamic systems by adding a feedback path such that the neural network's output becomes dependent on the previous states. However, gradient vanishing problems, in addition to difficulty in processing long sequences, limits RNN performance, especially in time-series forecasting problems[42].

Long Short-Term Memory (LSTM) is developed to solve previously discussed RNN shortcomings with the ability to learn long and short-term dependencies. LSTM encompasses series-connected memory blocks where each block, as depicted in Figure 4.3, consists of three gates: forget gate (f), input gate (i), and output gate (o).

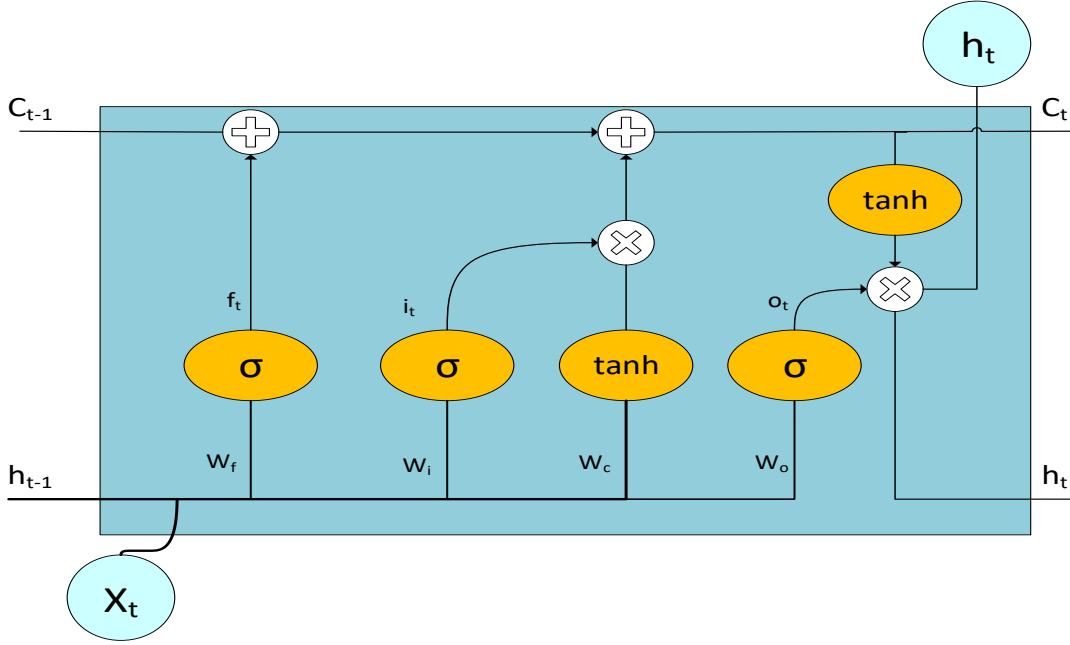


Figure 4. 3: LSTM block

Based on the previous value of hidden state h_{t-1} and x_t . Forget gate evaluates which information of cell state C_{t-1} to be thrown away. The block equation can be written as follows [43]:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (4.2)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (4.3)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (4.4)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_c[h_{t-1}, x_t] + b_i) \quad (4.5)$$

$$h_t = o_t * \tanh(C_t) \quad (4.6)$$

Where W_i , W_f , W_c , and W_o represent the weight matrices while b_i , b_f , b_c , and b_o denote biases, and σ is a sigmoid activation function.

Hence, the proposed model consists of two blocks, as shown in figure 4.4. The first block has a feedforward neural network to estimate the fouling while the second one is used to predict the fouling for several time steps ahead.

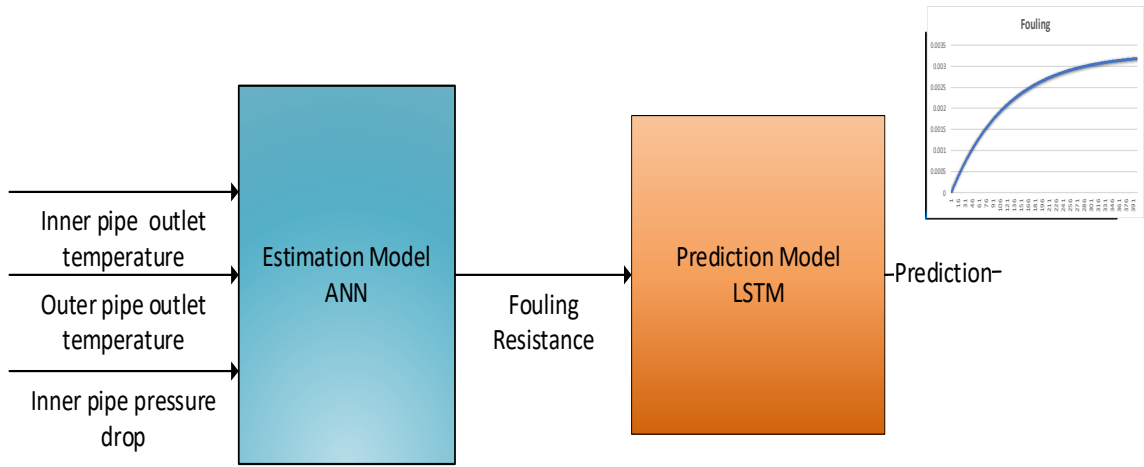


Figure 4. 4: The proposed model architecture

4.4 Results and Discussion

The counter flow DPHE model has been numerically simulated in MATLAB to generate the data based on the parameters illustrated in table 4.1. An asymptotic fouling build-up pattern is considered as demonstrated in figure 4.5. Water was used as a fluid for both the inner and outer pipes in the simulated DPHE. MATLAB deep learning toolbox has been adopted to implement an ANN with 20 hidden neurons depicted in figure 4.2. The inner pipe pressure drop, the inner and outer pipe outlet temperatures shown on figures 4.6.and

4.7, respectively, are selected as ANN inputs, whereas the fouling estimated resistance represents the ANN model's output.

Table 4. 1: The Parameters of Simulated DPHE

Hot fluid mass flow rate ($\dot{m}_h$)	0.1 Kg/sec
Cold fluid mass flow rate ($\dot{m}_c$)	0.0552 Kg/sec
Specific heat at a constant pressure of hot fluid (C_{ph})	4180 J/Kg.K
Specific heat at a constant pressure of cold fluid (C_{pc})	4180 J/Kg.K
Hot fluid density (ρ_h)	1000 Kg/m ³
Cold fluid density (ρ_c)	1000 Kg/m ³
Length of pipe	5 m
Overall heat coefficient (U)	1000 W/m ² .K
Number of segments (M)	50
Time step	0.01 sec
Hot side inlet temperature	100°C
Cold side inlet temperature	20°C
Inner diameter of the inner pipe (d_i)	0.04m
Outer diameter of the inner pipe (d_o)	0.05m
Inner diameter of the outer pipe (D_i)	0.1m
Roughness of fluid inner surface (k_s)	0.001 m
Thermal conductivity of fouling material	0.1 W/m.K

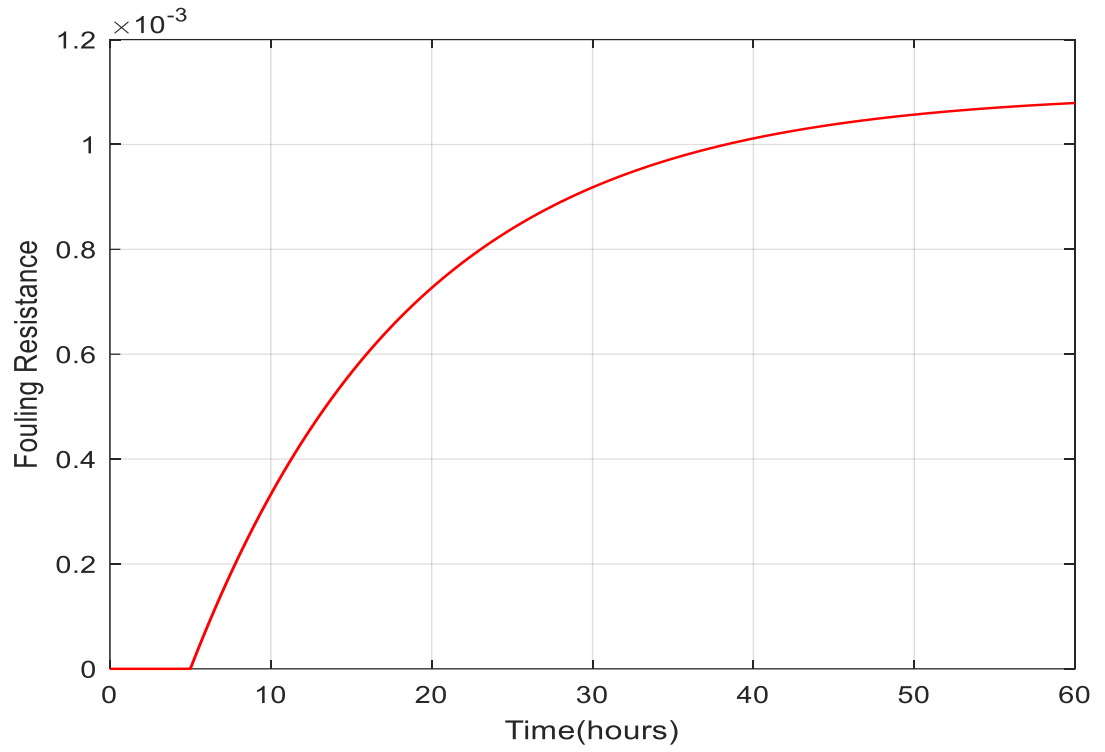


Figure 4. 5: Inner pipe fouling curve

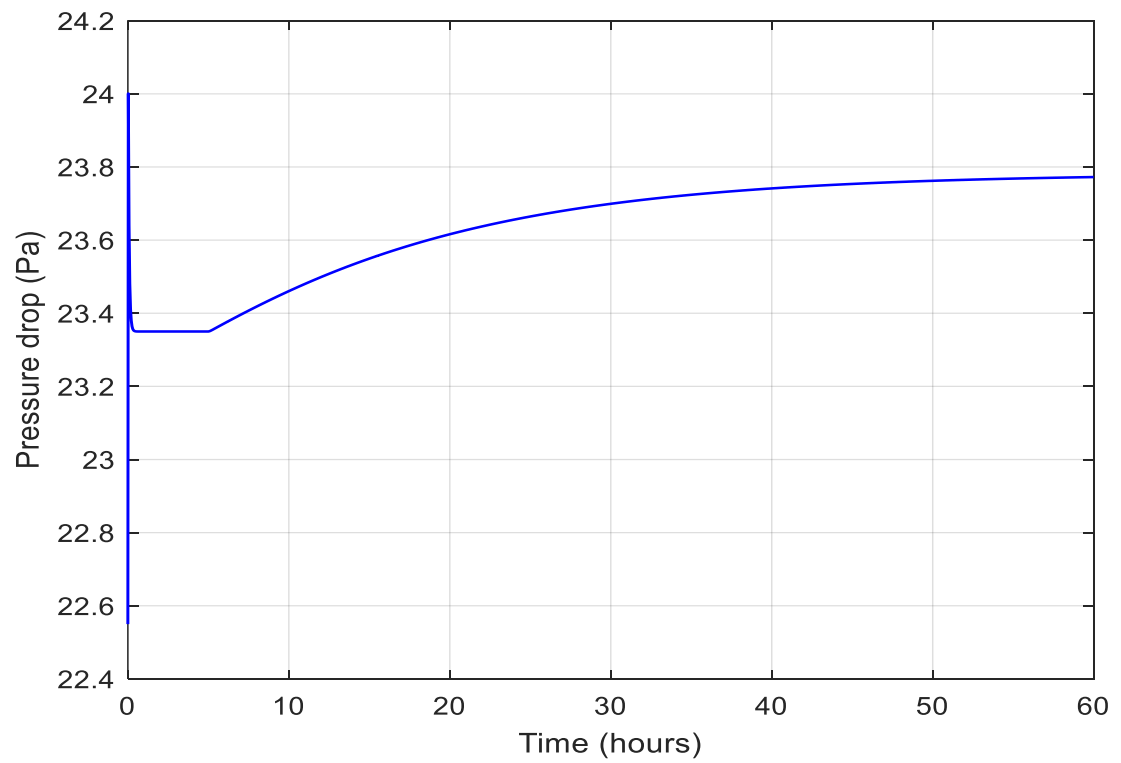


Figure 4. 6: Counter flow DPHE inner pipe pressure drop

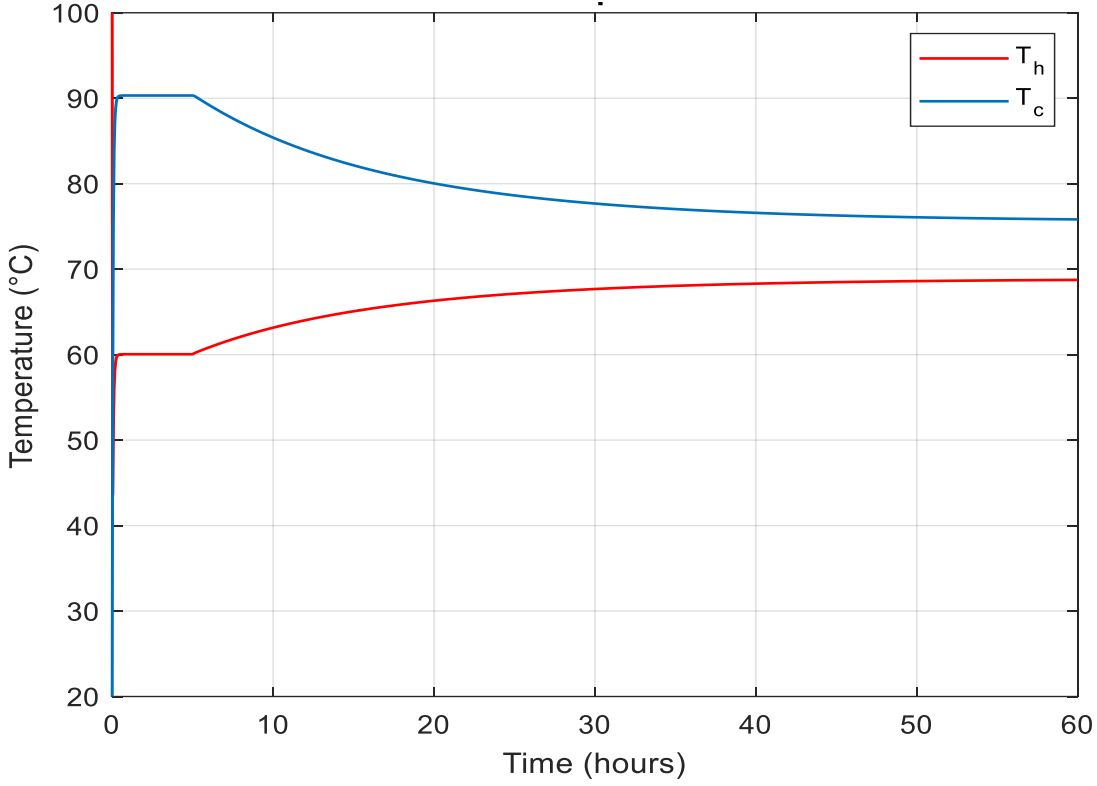


Figure 4. 7: Counter flow DPHE open-loop response

Before training the fouling estimation model, the obtained data firstly was normalized within the range (-1, 1), then it has been divided into three groups: training, validation, and testing with ratios 70%,15%, and 15%, respectively. Figure 4.8 demonstrates the training performance whereas a tiny error is obtained with a mean squared error (MSE)= 8.15×10^{-11} where MSE is given by the following equation

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2 \quad (4.7)$$

N denotes the number of data points, $\hat{Y}$ is the estimated value, and Y represents the observed value.

Figure 4.9 shows the ANN regression performance on the training, validation, and testing sets, as well as the overall performance where approximately a one to one matching is obtained.

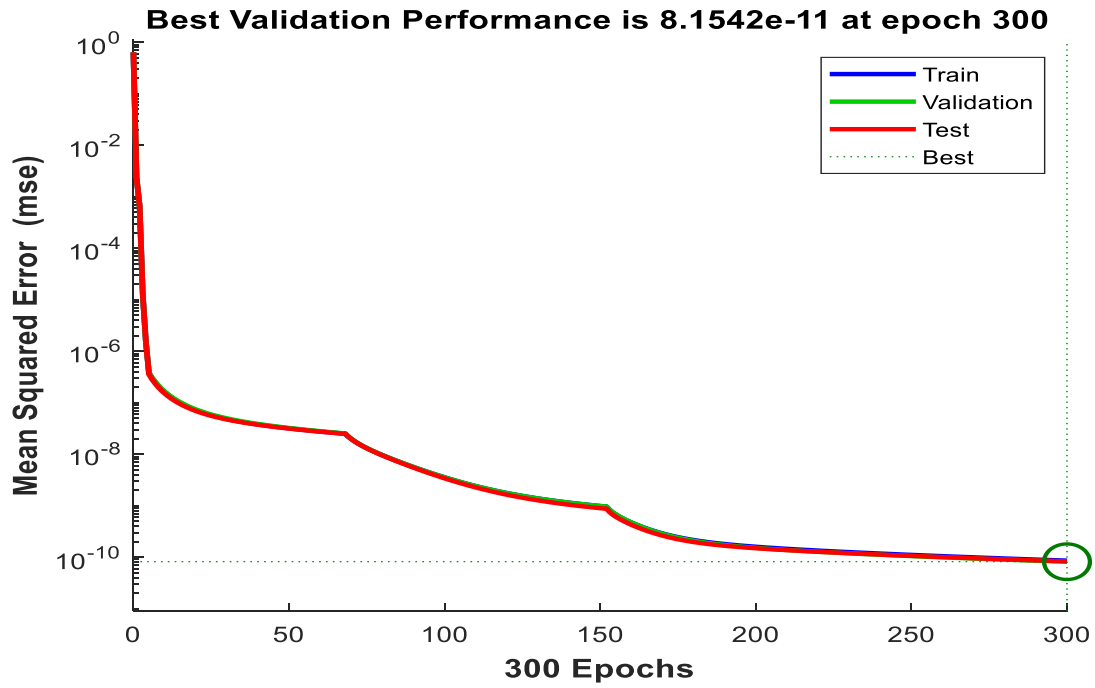


Figure 4. 8: Training performance

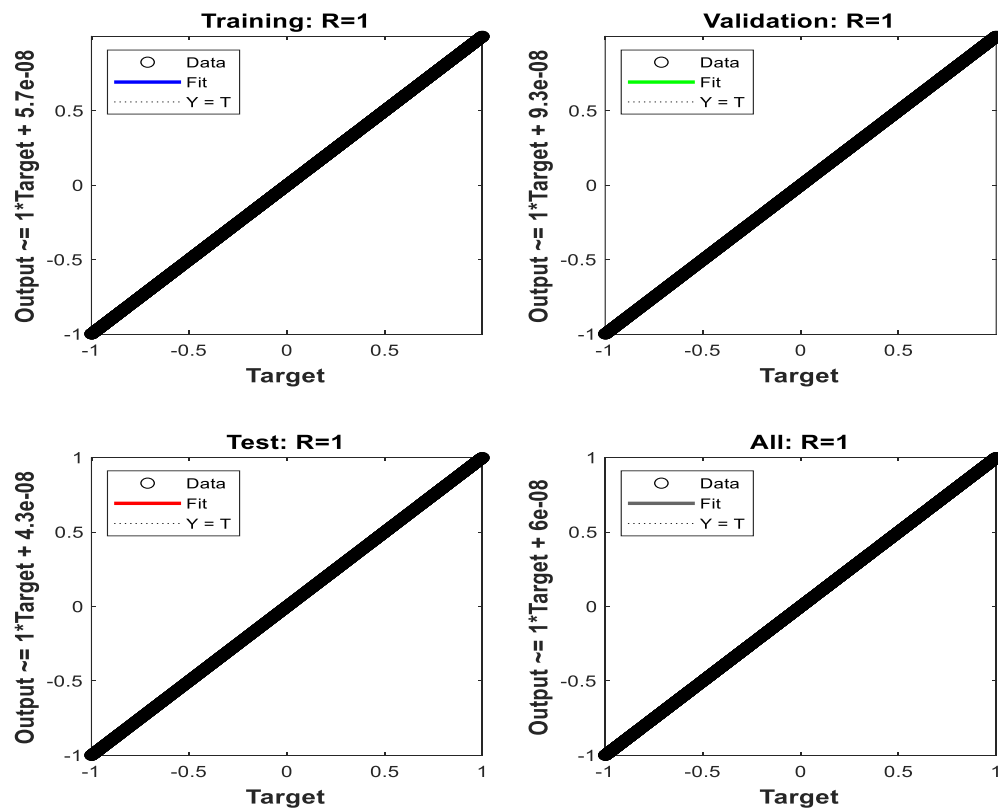


Figure 4. 9: ANN regression performance

The estimated fouling factor obtained from ANN was considered as an LSTM input, which has 15 hidden neurons.

The LSTM is trained on the first 90% of the observed or estimated data, where the data is downsampled to one sample every five minutes; then, the LSTM model used to predict the remaining 10% of the data. Figure 4.10 illustrates the training progress performance where LSTM showed a prediction error $RMSE = 3.85 \times 10^{-4}$ which represents a reasonable error considering short term prediction. Figure 4.11 depicts the fouling resistance prediction performance, which can help in providing early alarms about DPHE's future status.

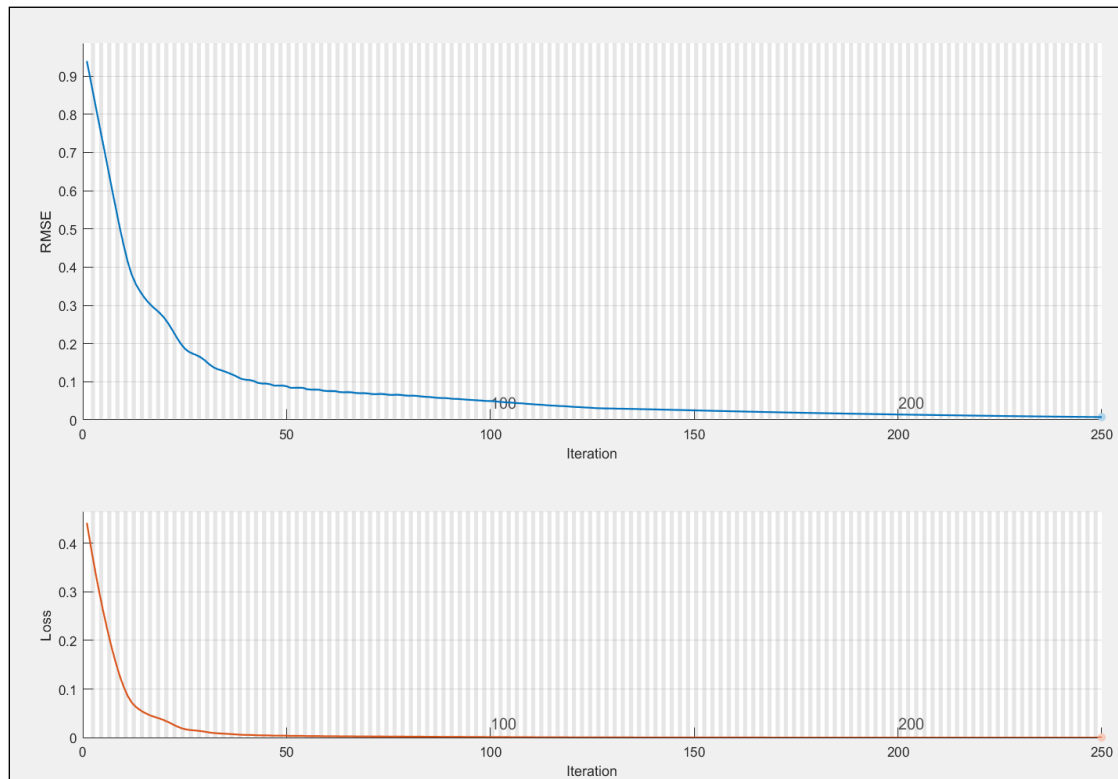


Figure 4. 10: The LSTM training performance

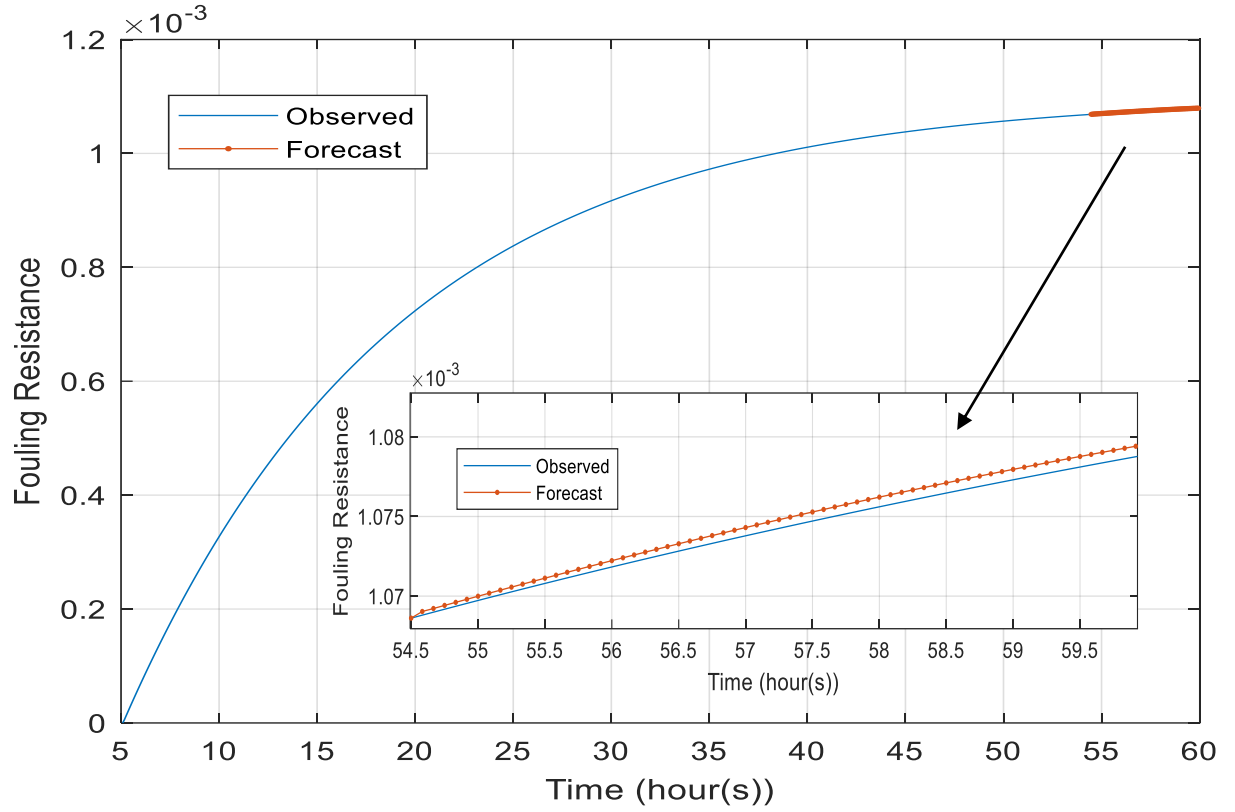


Figure 4. 11: Fouling prediction performance

4.5 Conclusion

A data-driven model based on ANN has been developed for fouling resistance estimation and prediction for the inner pipe fouling in DPHE. The model requires only the measurements of pressure drop beside the inner and outer pipe outlet temperatures. Simulation data used for model training and validation, where an asymptotic fouling regime is adopted for data generation. The suggested model showed an excellent estimation capability with $MSE= 8.15 \times 10^{-11}$ in addition to an accurate short-term prediction with $RMSE= 3.85 \times 10^{-6}$.

CHAPTER 5

Heat Exchanger Fouling Compensation

5.1 Introduction

This chapter investigates the possibility of compensating the inner pipe fouling in counter flow double pipe heat exchangers. Two feedback control schemes have been employed to achieve this purpose based on the numerical model presented in chapter 3. The feedback controller is responsible for regulating the hot fluid outlet temperature around a certain setpoint by manipulating the cold fluid flow rate subjected to an inner tube fouling build-up. Fouling leads to the deterioration in the heat transfer coefficient, which severely affects the heat exchanger outlet temperatures; thus, the controller should be able to resist fouling thermal effect as well as variations in the other process parameters, including inlet temperatures and flowrates.

Due to the nonlinearity and distributed parameters nature of the DPHE model, it is challenging to develop a controller based on the system's equations. Two control schemes have been adopted. Firstly, a PID controller optimized by Harmony search (HS) metaheuristic algorithm is used to manipulate the DPHE cold fluid flow rate. Then a fuzzy logic controller (FLC) is adopted to control the rate of change in cold fluid flowrate based on the temperature error. Finally, these two control schemes have been compared under several operating scenarios.

5.2 PID Parameters Optimization Using Harmony Search Algorithm

PID controller is known for its simplicity, ease of realization, and functionality, so it has been extensively used in numerous industrial systems[44]. Several Model-based and

model-free tuning methods have been developed to tune the PID controller[45]. However, these tuning strategies might not lead to optimal performance, especially when the controlled plant is nonlinear.

Based on the discrete-time model of the DPHE presented in chapter 3 a discrete PID controller has been utilized to manipulate the cold fluid mass flow rate according to the desired hot fluid outlet temperature. The mathematical formula for a discrete-time PID controller output is given by

$$u_t = \left(k_p + k_i \frac{T_s}{1-z^{-1}} + K_d \frac{1}{T_s} (1 - z^{-1}) \right) e_t \quad (5.1)$$

Where k_p is the proportional gain, k_d is the derivative gain and k_i is the integral gain while e denotes the error, T_s represents the sampling time, and z is a backward shift operator[46].

Figure 5.1 illustrates the block diagram of the PID controlled counter flow DPHE.

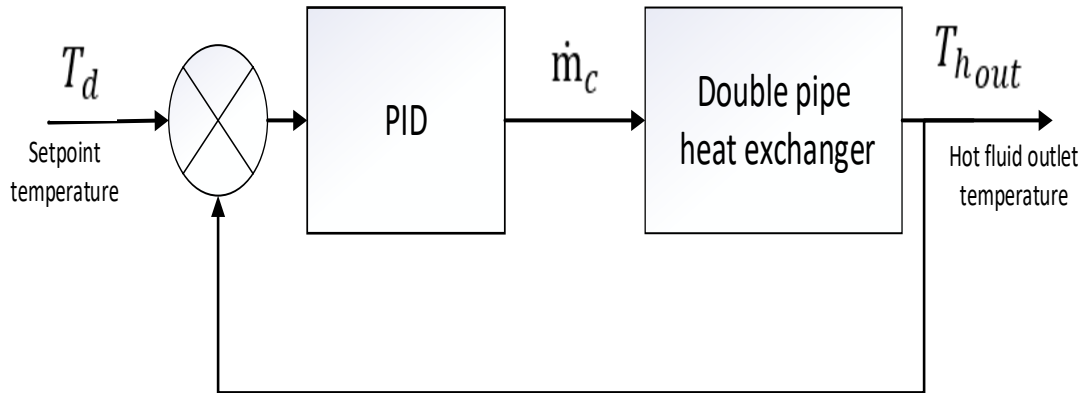


Figure 5. 1: PID controlled DPHE block diagram.

Harmony Search Algorithm (HSA) is a recent population-based musical inspired meta-heuristic algorithm suggested by Geem in [47]. HSA simulates music improvisation

behavior, which represents the activity of finding the best harmony by trying different pitches combinations. This improvisation is implemented in HSA in the selection process where the values of new harmony can be selected from Harmony Memory (HM) which is the place where HSA keeps the solution set, or from HM but with a slight modification, or it can be selected randomly from the admissible range of values [48],[49]. This process is directed through two vital parameters: Pitch Adjusting Rate (PAR) $\in [0,1]$, which represents a slight adjustment of the HM's past value. The adjusted pitch is given by

$$x_{new} = x_{old} + FW \cdot \epsilon \quad (5.2)$$

Where FW is the fret width, and ϵ is a uniformly distributed random number in the range $[-1,1]$. x_{old} is the existing pitch in the HM, and x_{new} represents the adjusted pitch.

The second parameter is Harmony Memory Considering Rate (HMCR) $\in [0,1]$, which denotes the probability of choosing a candidate solution within the present members of HM. For small values of HMCR, a few elite harmonies only selected, and it may cause slow convergence. In contrast, at high values (near 1), the convergence is faster but may violate algorithm exploration capability. The flowchart of HS is shown in figure 5.2, which involves the following procedures[49],[50]:

- 1- Harmony memory initialization, where initial solutions in HM are generated randomly. An HM with a size of HMS can be implemented as:

$$HM = \begin{bmatrix} xm_1^1 & xm_2^1 & \dots & xm_n^1 \\ xm_1^2 & xm_2^2 & \dots & xm_n^2 \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \dots & \vdots \\ xm_1^{HMS} & xm_2^{HMS} & \dots & xm_n^{HMS} \end{bmatrix} \quad (5.3)$$

Where $[xm_1^i, xm_2^i, \dots, xm_n^i]$ are the candidate solutions ($i=1, 2, \dots, HMS$).

- 2- Improvisation of new harmony from the HM according to HMCR and PAR, which resemble crossover and mutation probability in the genetic algorithm (GA).
- 3- Update of HM. The new harmony from step 2 is compared with the worst harmony in the HM, and if the new harmony is fitter, it will supersede the worst one in HM; otherwise, it will be eliminated.
- 4- Return to step 2 if the termination criteria is not satisfied.

The implemented algorithm is based on the original HS algorithm, but instead of generating only one harmony at each improvisation, multiple harmonies are generated to enhance convergence speed. This modification introduced in[51]. Also, dynamic FW has been used according to the following equation [52].

$$FW(i) = FW_{\max} \exp\left(\ln\left(\frac{FW_{\min}}{FW_{\max}}\right) * \frac{it}{NI}\right) \quad (5.4)$$

Where $FW_{\max}$ is the maximum fret width, $FW_{\min}$ is the minimum fret width, NI is the number of generations, and it is the current generation number. Dynamic FW has a large value at the beginning to enhance global search capability, and it decreases gradually versus iteration such that it has a small value at the end of iterations to enhance local search capability.

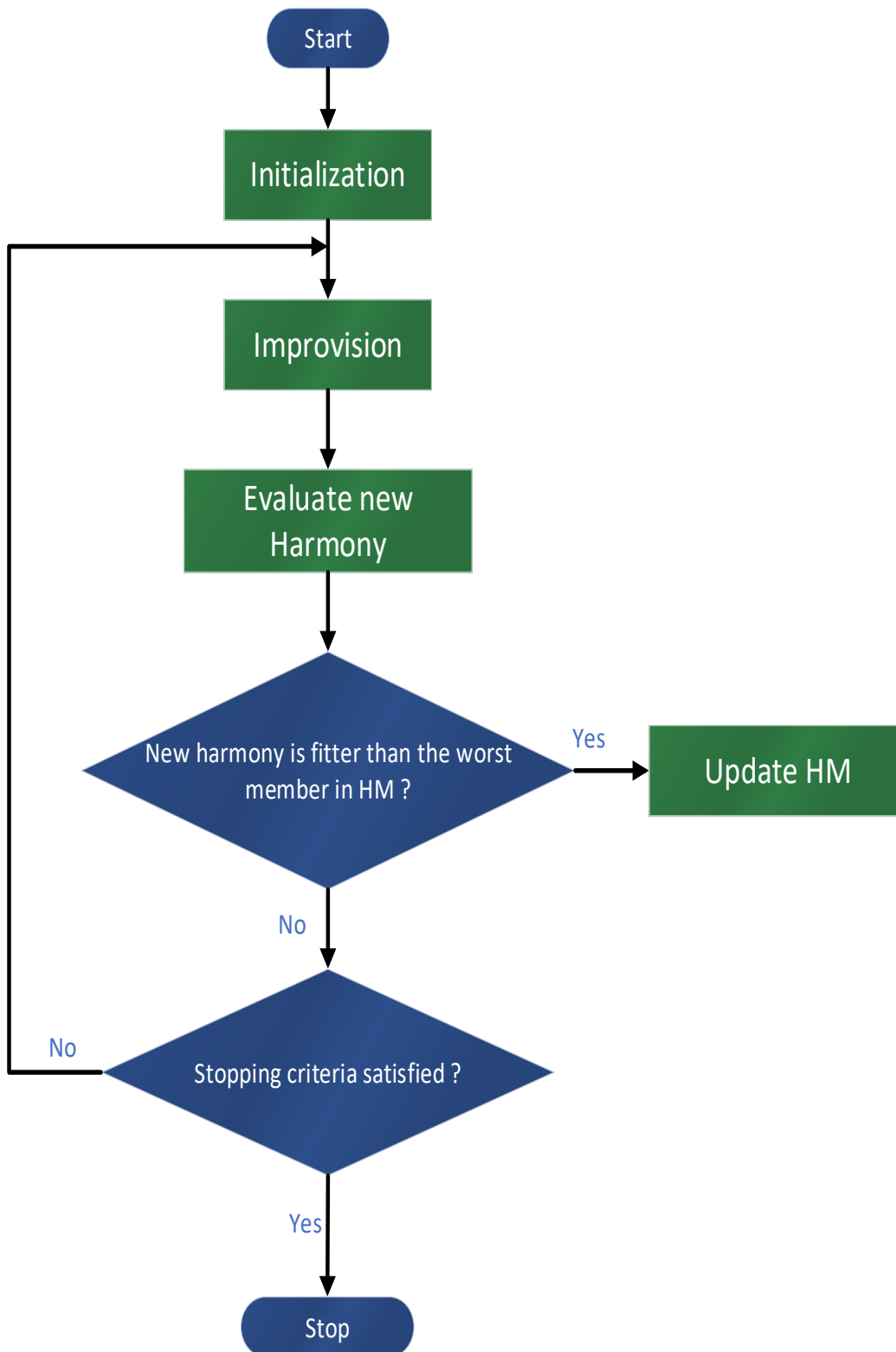


Figure 5. 2: Harmony search algorithm flowchart

5.3 Fuzzy Logic Controller

Fuzzy logic control is one of the brilliant applications of fuzzy set theory, which in contrast to a crisp set, allows partial membership (i.e., an element can be partially a member of more than one set at the same time). Fuzzy logic controller (FLC) is a heuristic controller that maps input vectors into a scalar output by using a linguistic expression in the format of If-Then rules obtained from utilizing human expertise[53]. The typical architecture of fuzzy control systems is represented in figure 5.3, which composes four principles elements:

- (1) Fuzzification, where the controller inputs are mapped to linguistic expressions.
- (2) Rule-base which consists of rules in IF-THEN format.
- (3) Inference mechanism, which infers fuzzy control action from the knowledge of linguistic variables and control rules.
- (4) Defuzzification where the fuzzy output of inference mechanism is transferred into a numerical value to control the process [53]

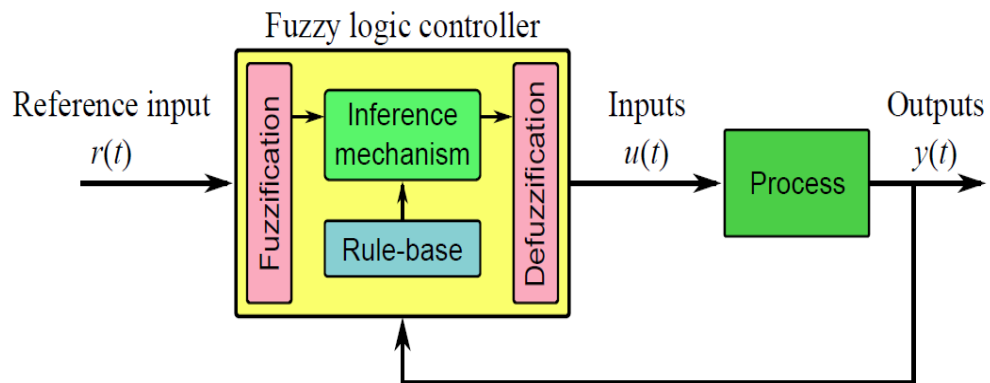


Figure 5. 3: Fuzzy logic control system structure

The fuzzy controller has been designed to control the DPHE inner pipe outlet temperature, which represents the hot fluid in this case study. The error between desired and actual inner pipe outlet temperature besides the rate of change of this error represents the controller inputs where the controller's output is the rate of change in the outer pipe fluid (cold fluid) mass flow rate $\Delta\dot{m}_c$. The proposed FLC architecture is demonstrated in figure 5.4 where $\dot{m}_c$ is evaluated as follows

$$\dot{m}_c(t) = \dot{m}_c(t - 1) + \alpha\Delta\dot{m}_c \quad (5.5)$$

Where α is a positive constant that controls the convergence speed.

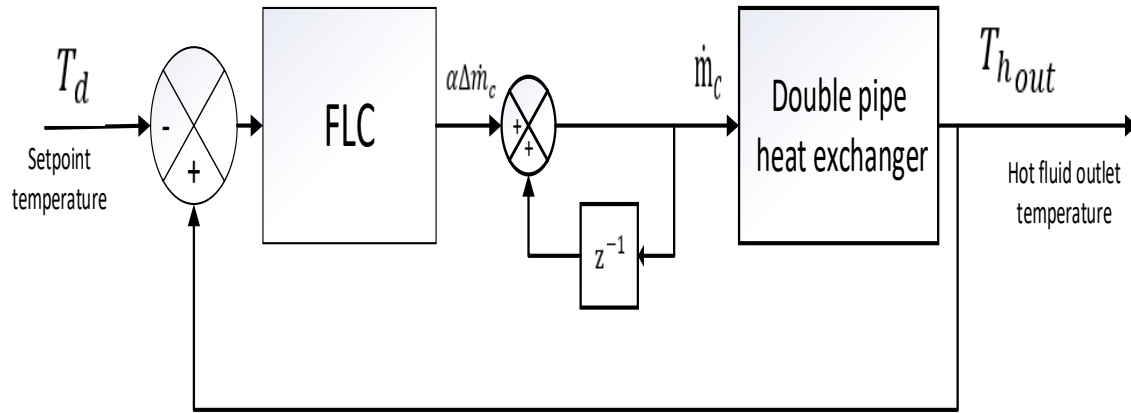


Figure 5. 4: The proposed FLC architecture

Triangular membership functions are adopted for fuzzy inputs and output with an input universe of discourse as follows [Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM) Positive Big (PB)]. The output has a similar universe of discourse by replacing PB and NB with PL and NL, respectively. Figures 5.5 and 5.6 show the proposed membership functions for inputs and output of the fuzzy controller. Table 5.1 depicts the rules used to design the fuzzy controller.

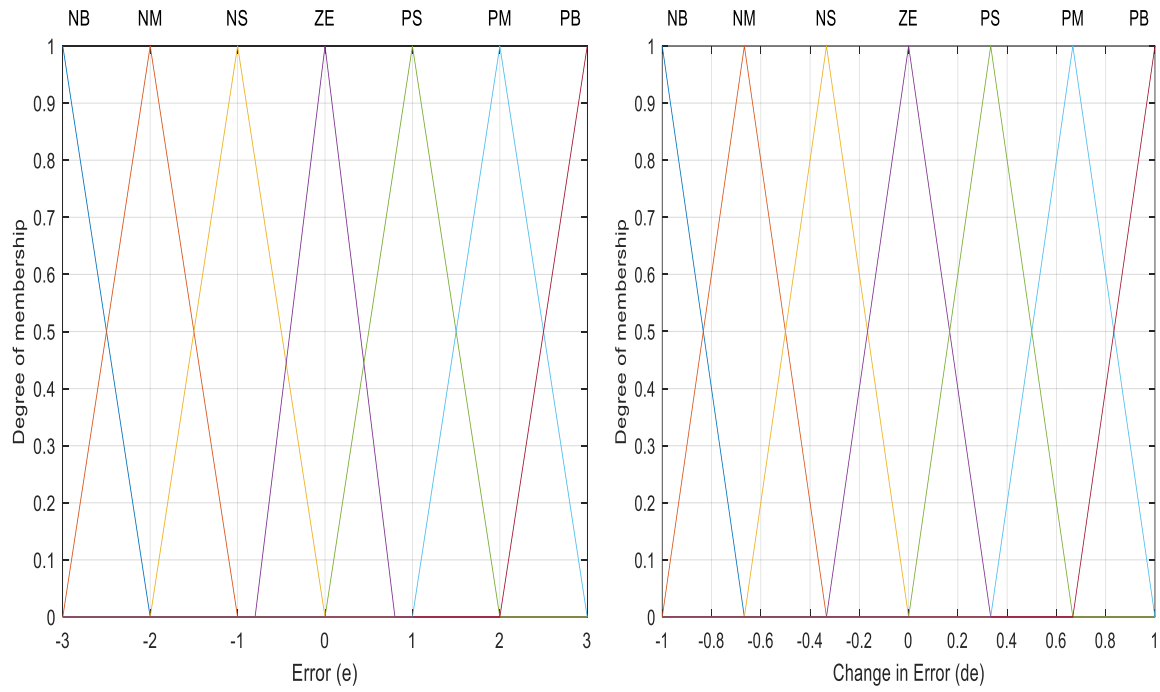


Figure 5. 5: Inputs' membership functions

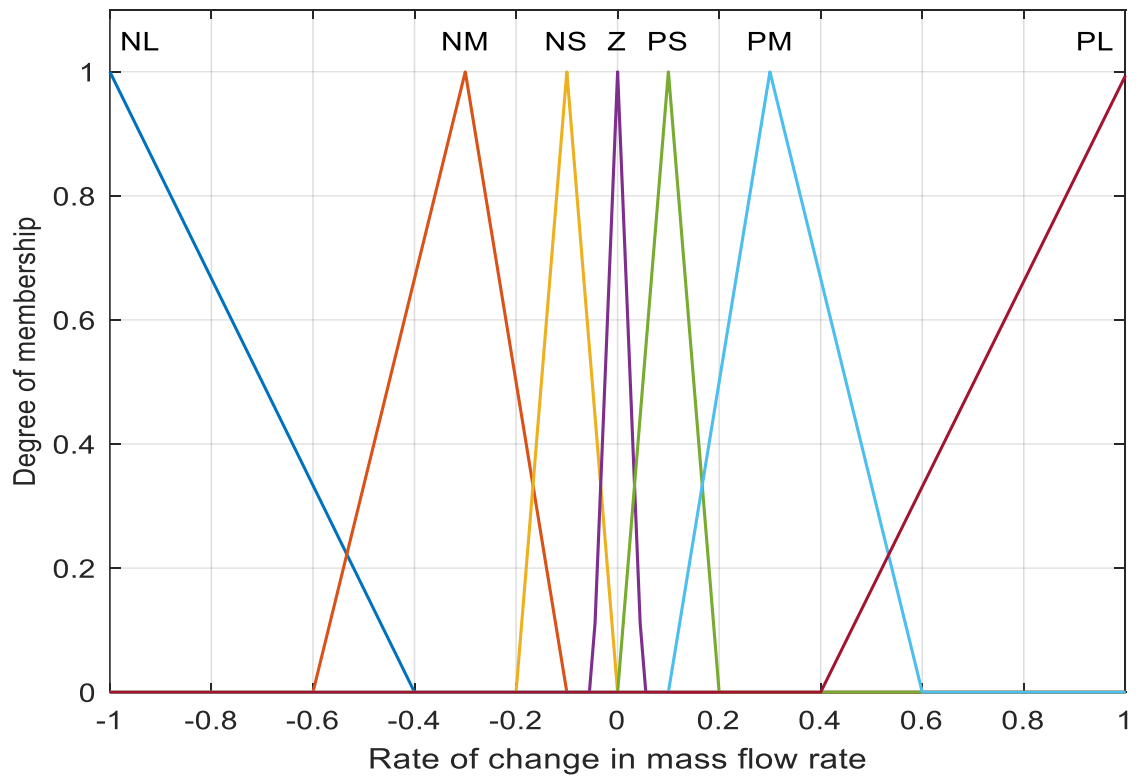


Figure 5. 6: Output's membership functions

Table 5. 1: FLC Rules

Output $\Delta \dot{m}_c$		Change in error $\dot{e}$						
		<i>NB</i>	<i>NM</i>	<i>NS</i>	<i>Z</i>	<i>PS</i>	<i>PM</i>	<i>PB</i>
Error <i>e</i>	<i>NB</i>	<i>NL</i>	<i>NL</i>	<i>NL</i>	<i>NM</i>	<i>NS</i>	<i>NS</i>	<i>Z</i>
	<i>NM</i>	<i>NL</i>	<i>NL</i>	<i>NM</i>	<i>NS</i>	<i>NS</i>	<i>NS</i>	<i>NS</i>
	<i>NS</i>	<i>NM</i>	<i>NS</i>	<i>NS</i>	<i>NS</i>	<i>Z</i>	<i>PS</i>	<i>PS</i>
	<i>Z</i>	<i>NM</i>	<i>NS</i>	<i>NS</i>	<i>Z</i>	<i>PS</i>	<i>PS</i>	<i>PM</i>
	<i>PS</i>	<i>NS</i>	<i>NS</i>	<i>Z</i>	<i>PS</i>	<i>PS</i>	<i>PM</i>	<i>PM</i>
	<i>PM</i>	<i>Z</i>	<i>Z</i>	<i>PS</i>	<i>PS</i>	<i>PS</i>	<i>PM</i>	<i>PL</i>
	<i>PB</i>	<i>PS</i>	<i>PS</i>	<i>PM</i>	<i>PM</i>	<i>PL</i>	<i>PL</i>	<i>PL</i>

Figure 5.7 reveals the internal structure of the designed FLC, where K1 and K2 are positive constants that control the controller sensitivity to the error (*e*) and the change in error (Δe), while α is a scaling factor. This structure resembles the conventional PD controller so that sometimes this structure is called a fuzzy-PD controller[54].

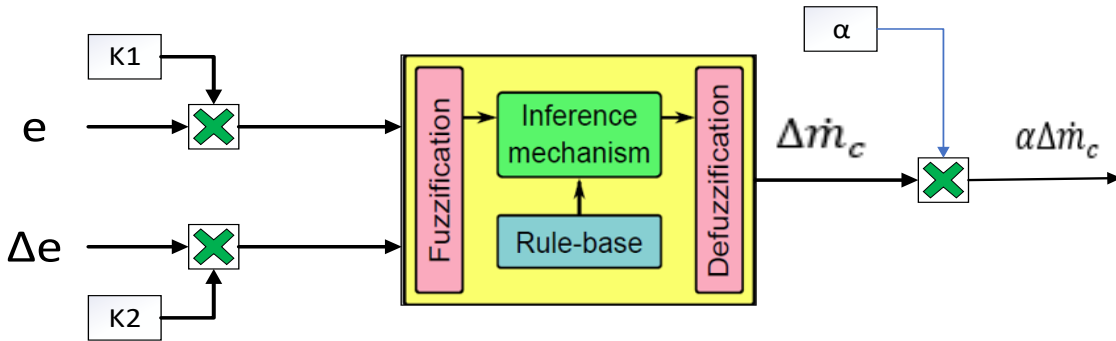


Figure 5. 7: FLC internal structure

The design parameter α controls the FLC adaptation speed which also indirectly affects both the performance and robustness of the controller. A very small α leads to slow response while a large α increases overshoot and can lead to instability in the system response. Therefore, another fuzzy logic system used to adaptively tune α by controlling the rate of change in the adaptation parameter α based on the system state to balance between the response speed and the robustness. The fuzzy tuning system receives the error and change in error signals as inputs that have similar membership functions as depicted in figure 5.8 (a) while the fuzzy output is shown in figure 5.8 (b). Table 5.1 shows the tuning rules where the characters N, Z, and P denote negative, zero, and positive subsequently.

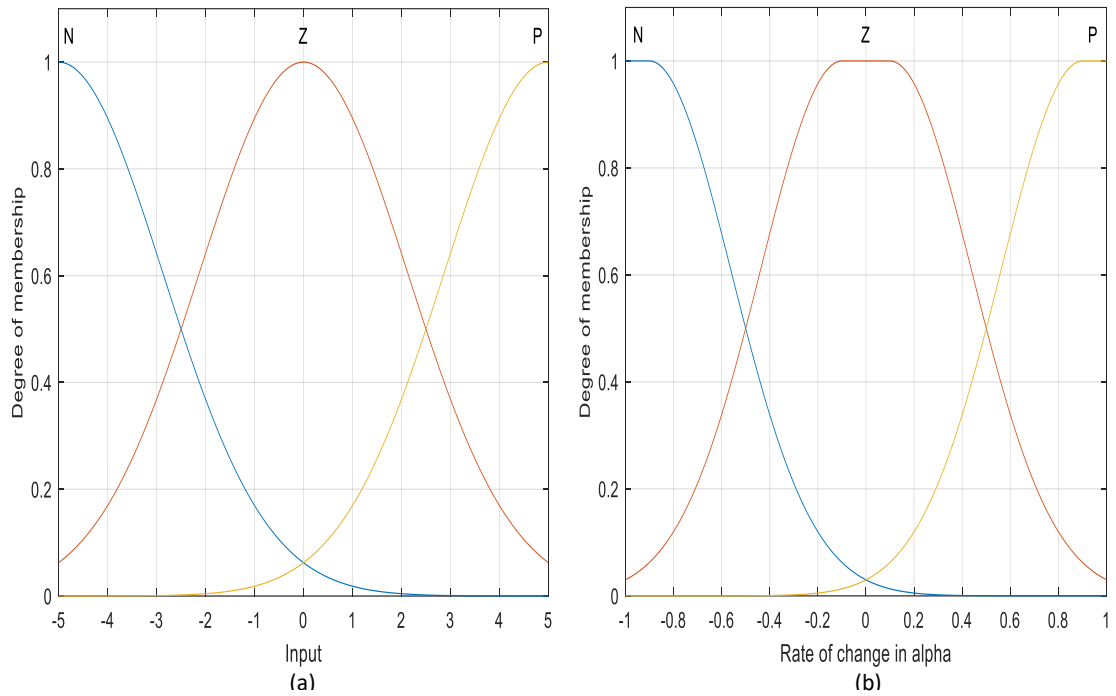


Figure 5. 8: input and output membership functions of adaption speed fuzzy tuner

Table 5. 2: Fuzzy Tuning System Rules

$\Delta\alpha$		$\dot{e}$		
		N	Z	P
e	N	P	P	N
	Z	P	N	P
	P	N	P	P

5.4 Results and Discussion

HSA used to tune PID parameters K_p , K_i , and K_d , by minimizing the cost function as revealed in equation (5.6) that is defined based on the Integral of Time multiplied Absolute Error (ITAE) and the standard deviation of the controller's output vector where the latter index penalizes the controller output chattering.

$$Cost\ Function = \frac{1}{N} \sum_{k=1}^N k|\epsilon(k)| + 10^3 * \sqrt{\frac{1}{N-1} \sum_{k=1}^N (u(k) - \mu)^2} \quad (5.6)$$

Where k represents time index and N denotes the number of samples while ϵ is the error between the actual hot fluid outlet temperature and the desired temperature ($\epsilon = T_{h_{out}} - T_d$) while μ denotes the mean value of the PID controller's output vector. The Error at the steady-state is more penalized than the error at the beginning because of the time multiplication term. The DPHE system is considered in its standard conditions based on the parameters shown in table 4.1, where the desired temperature is 60 °C and the simulation time is set to 3 hours. The optimized parameters are shown in table 5.2 whereas figure 5.9 reveals the HAS convergence.

Table 5. 3: PID Optimized parameters

Parameter	K_p	K_i	K_d
value	0.6553	0.0107	9.99

On the other hand, the fuzzy controller has been implemented according to the structure given in figure 5.7 with $K_1=1$, $K_2=25$, and $\alpha = 0.00015$.

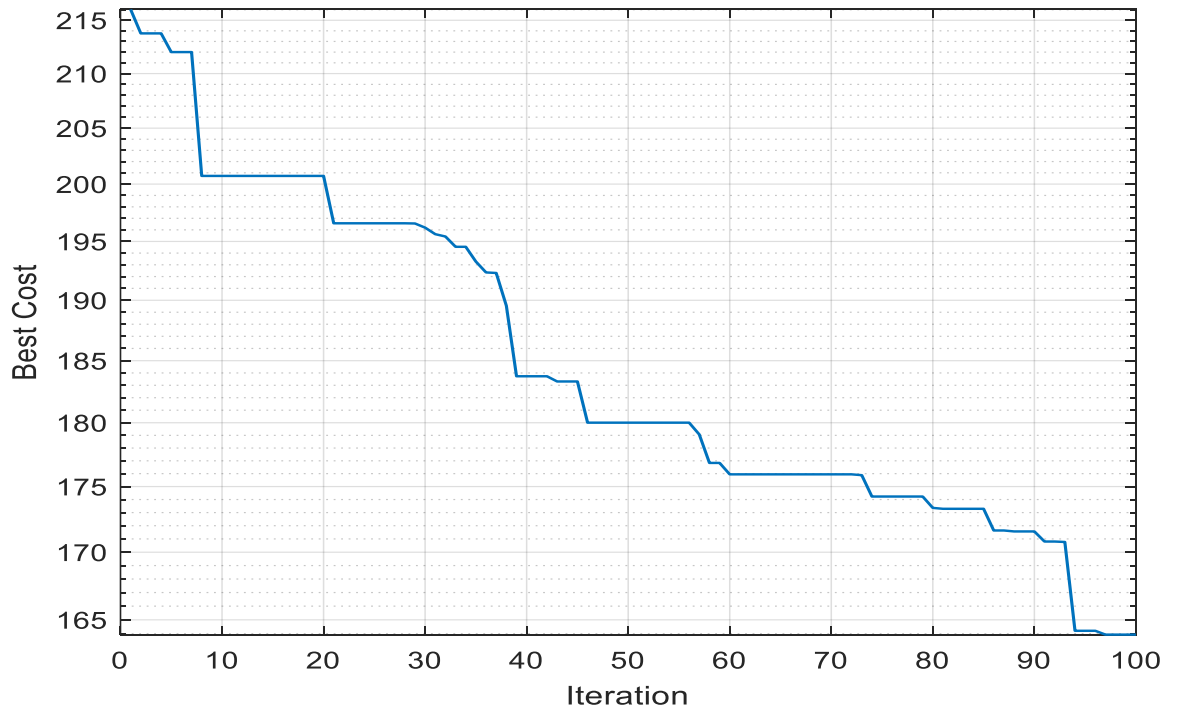


Figure 5. 9: HSA convergence

Six scenarios have been considered for evaluating both PID and fuzzy controllers to show the robustness of the designed controllers under different operation conditions. The controlled DPHE system has been simulated using MATLAB/SIMULINK.

5.4.1 The Operation Under Standard Conditions

In this scenario, the simulation is conducted based on the parameters given in table 4.1, where the reference outlet temperature of the hot fluid (inner pipe fluid) has been adjusted to 60°C . Figure 5.10 shows the hot fluid outlet temperature for both controllers, where both controllers exhibit decent dynamic performance with fast settling time. The PID has ITAE equals 100, where the ITAE is 126.53 for the FLC. Figures 5.11 and 5.12 illustrate the cold fluid mass flow rate obtained from the PID and FLC, respectively, where both FLC and PID controllers show a smooth output. The cold fluid outlet temperature is depicted in figure 5.13.

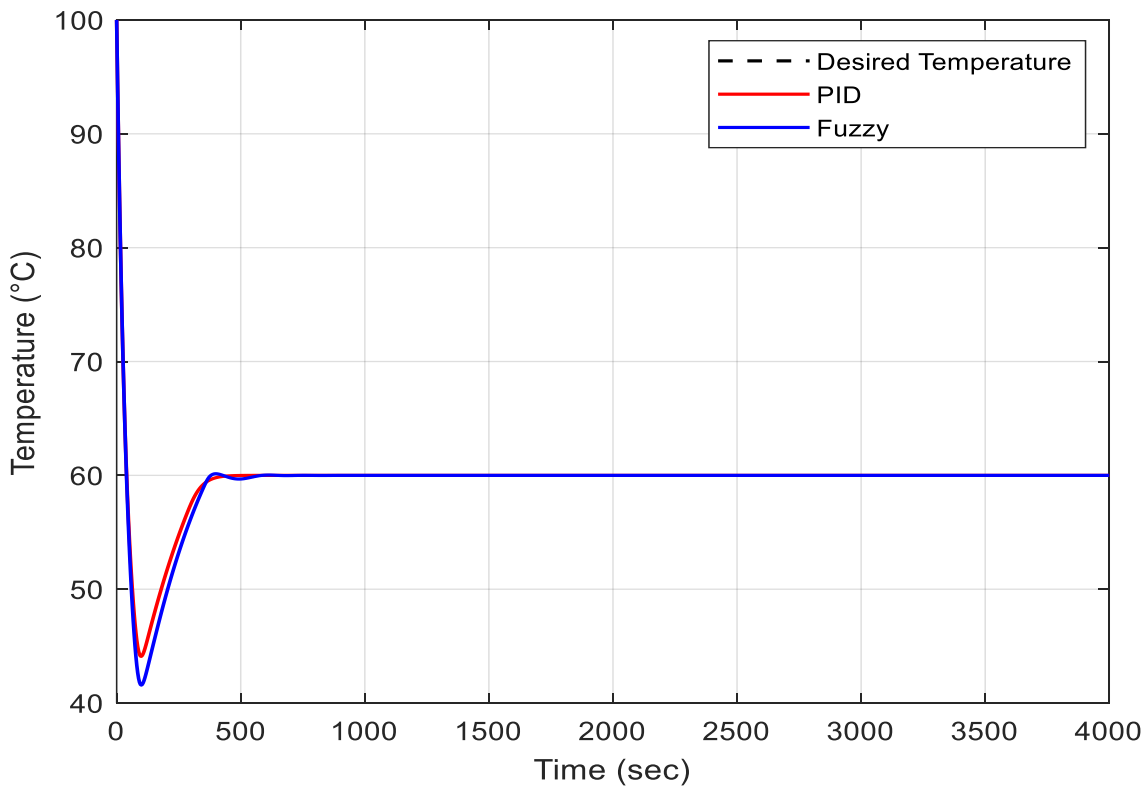


Figure 5. 10: Hot fluid outlet temperature under standard conditions

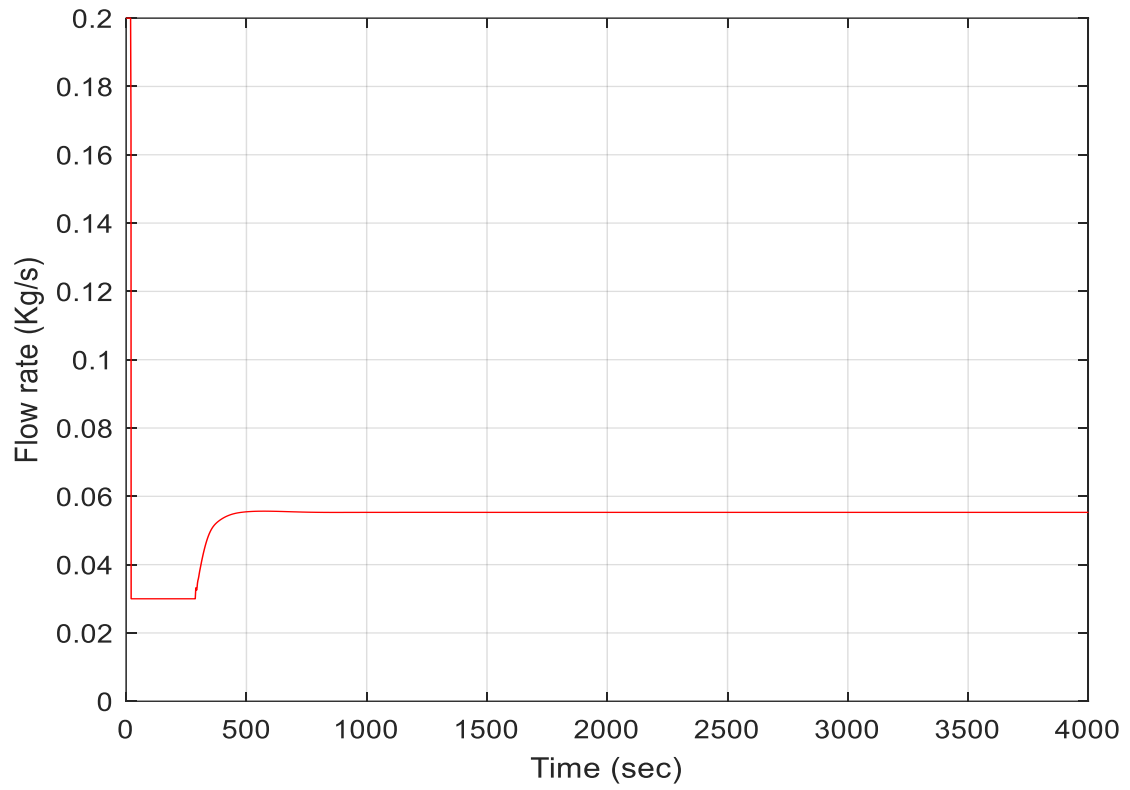


Figure 5. 11: Cold fluid mass flow rate under standard conditions (PID)

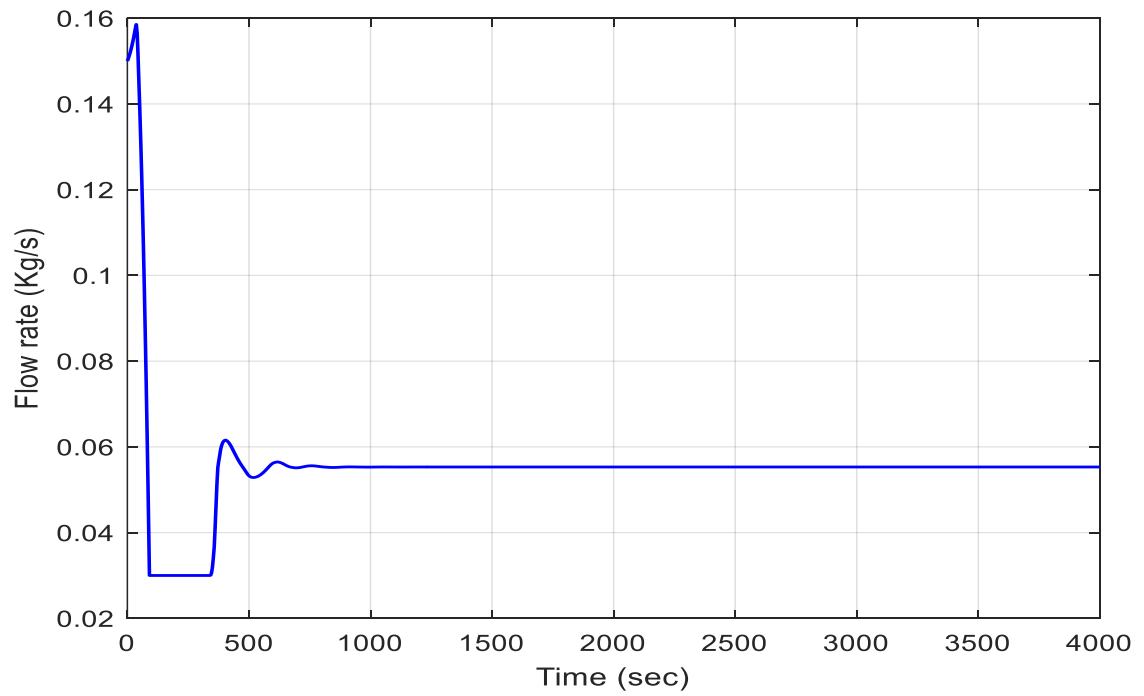


Figure 5. 12: Cold fluid mass flow rate under standard conditions (Fuzzy)

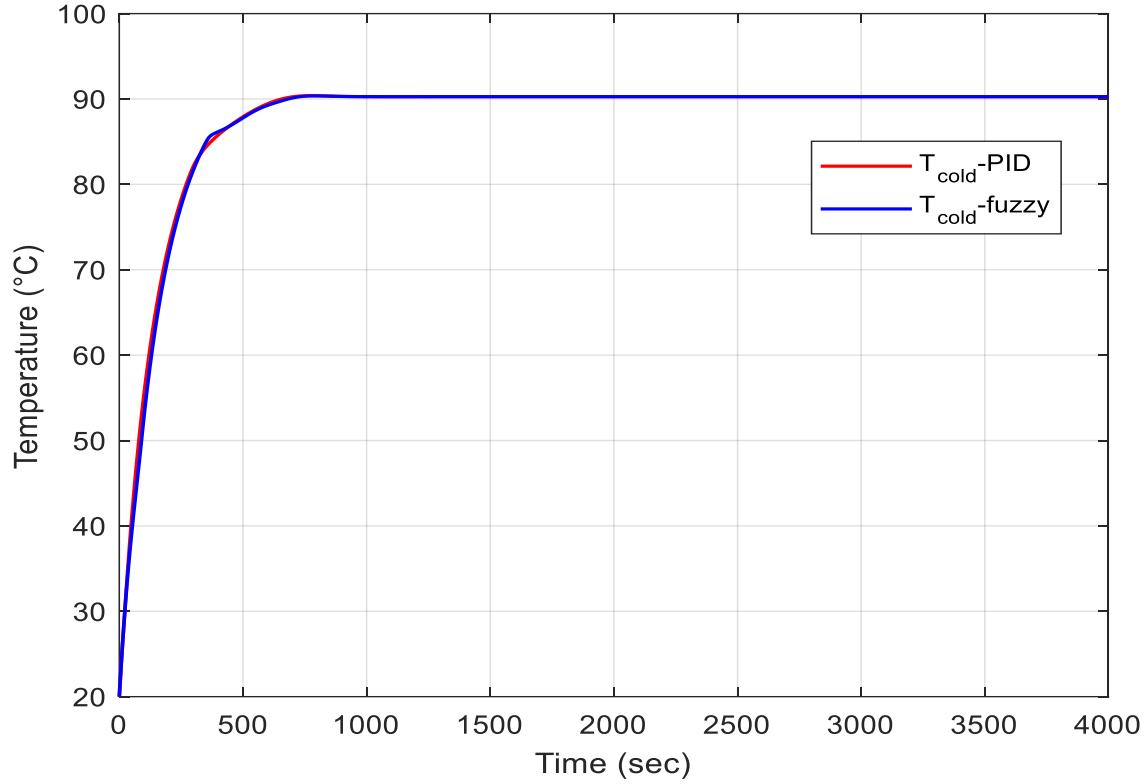


Figure 5. 13: Cold fluid outlet temperature under standard conditions

5.4.2 Varying Inner Pipe Outlet Temperature Setpoint

This scenario evaluates the dynamics of the controlled DPHE system subjected to a varying reference temperature. The simulation is conducted for five hours, where the reference temperature is altered from 60 to 55 then to 70 and finally returned to 60 °C at the end of simulation time. Figure 5.14 depicts the tracking performance of both controllers, where PID experiences abrupt changes during the transition period from one reference to another. The PID controller proved a better response with ITAE equals to 1684 while the FLC has a higher ITAE that equals 2903. FLC and PID controller outputs are shown in figures 5.15 and 5.16, respectively.

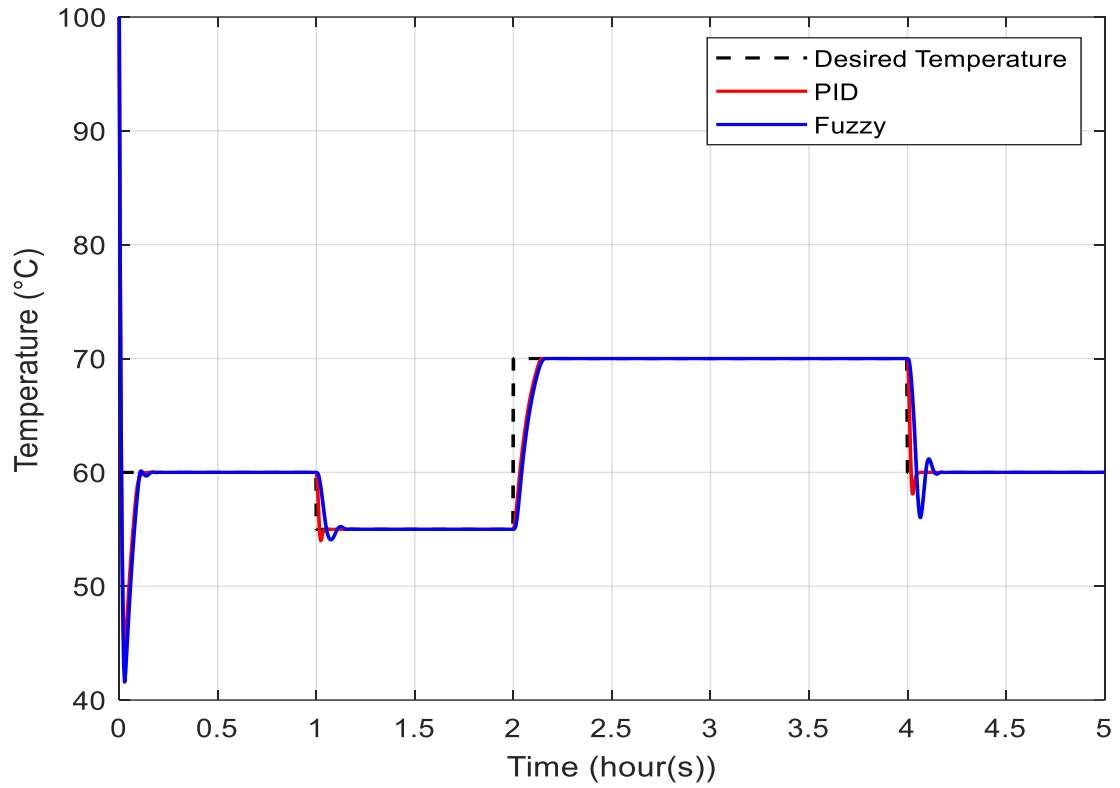


Figure 5. 14: Hot fluid outlet temperature under varying setpoint

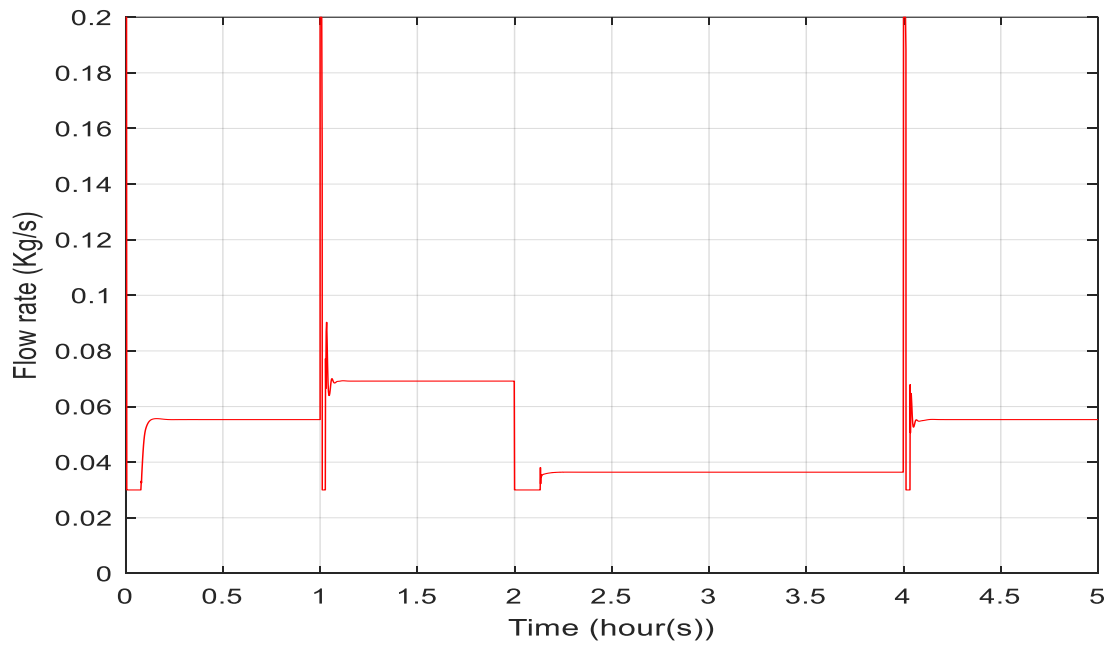


Figure 5. 15: Cold fluid mass flow rate under varying setpoint (PID)

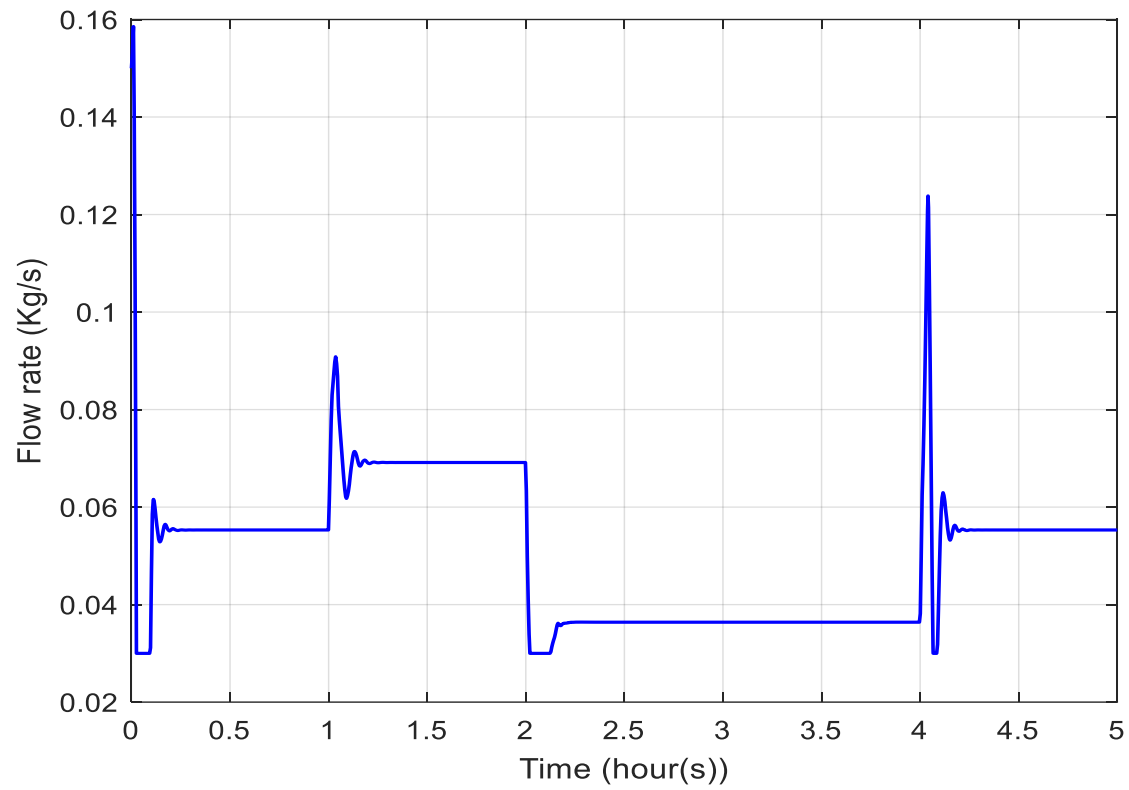


Figure 5. 16:Cold fluid mass flow rate under varying setpoint (Fuzzy)

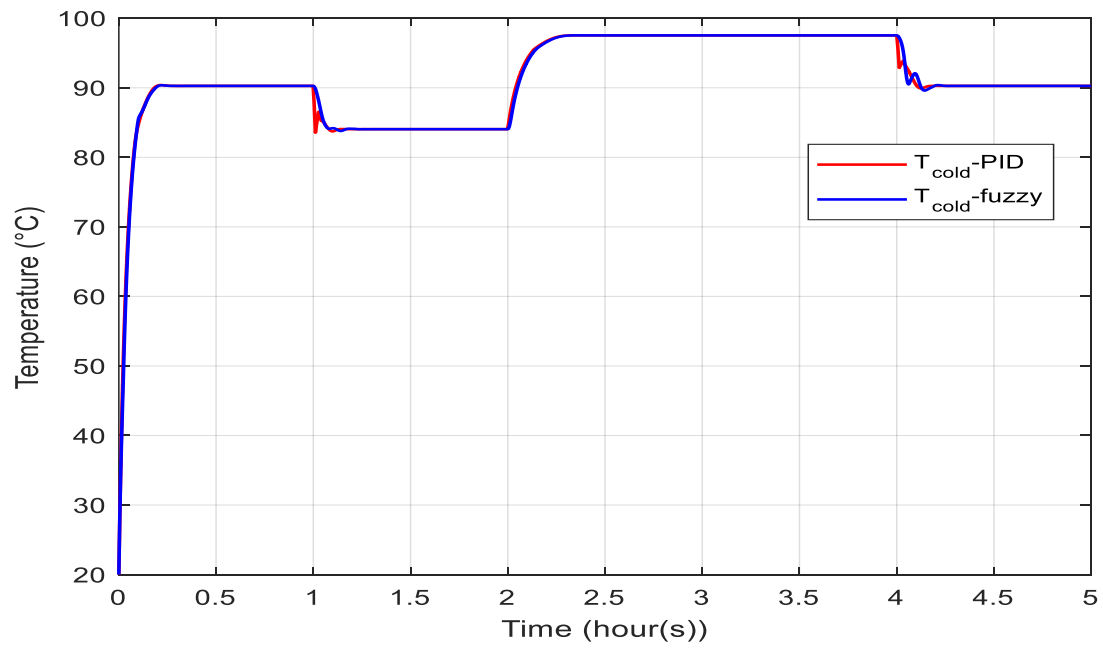


Figure 5. 17:Cold fluid outlet temperature under varying setpoint

5.4.3 Varying Inner Pipe Inlet Flow Rate

The inner pipe (hot) fluid mass flow rate has been varied, as illustrated in figure 5.18. Both controllers have absorbed the effect of change in mass flow rate as demonstrated in figure 5.19. The PID controller output is depicted in figure 5.20, while the outer pipe mass flow rate obtained by the FLC is shown in figure 5.21.

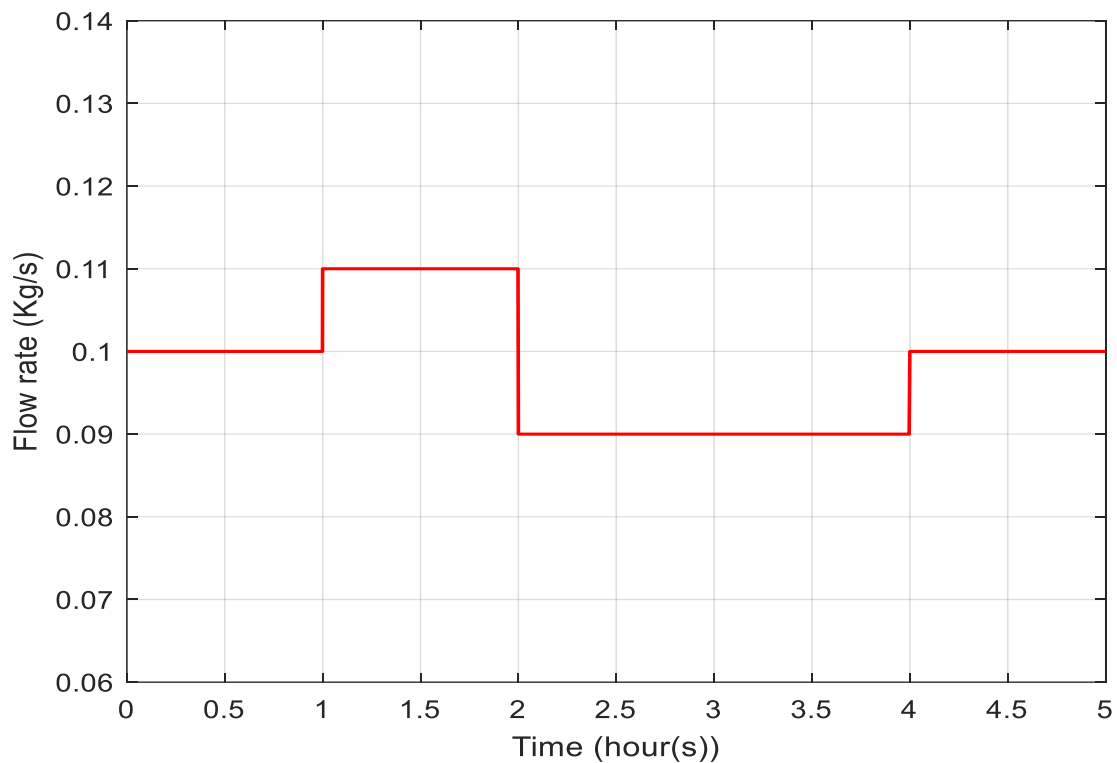


Figure 5. 18: Hot fluid mass flowrate

In terms of ITAE FLC recorded 388 while the PID controller recorded 122, which reveals that the PID performance is slightly better than the FLC in this scenario. The cold fluid outlet temperature is illustrated in figure 5.22.

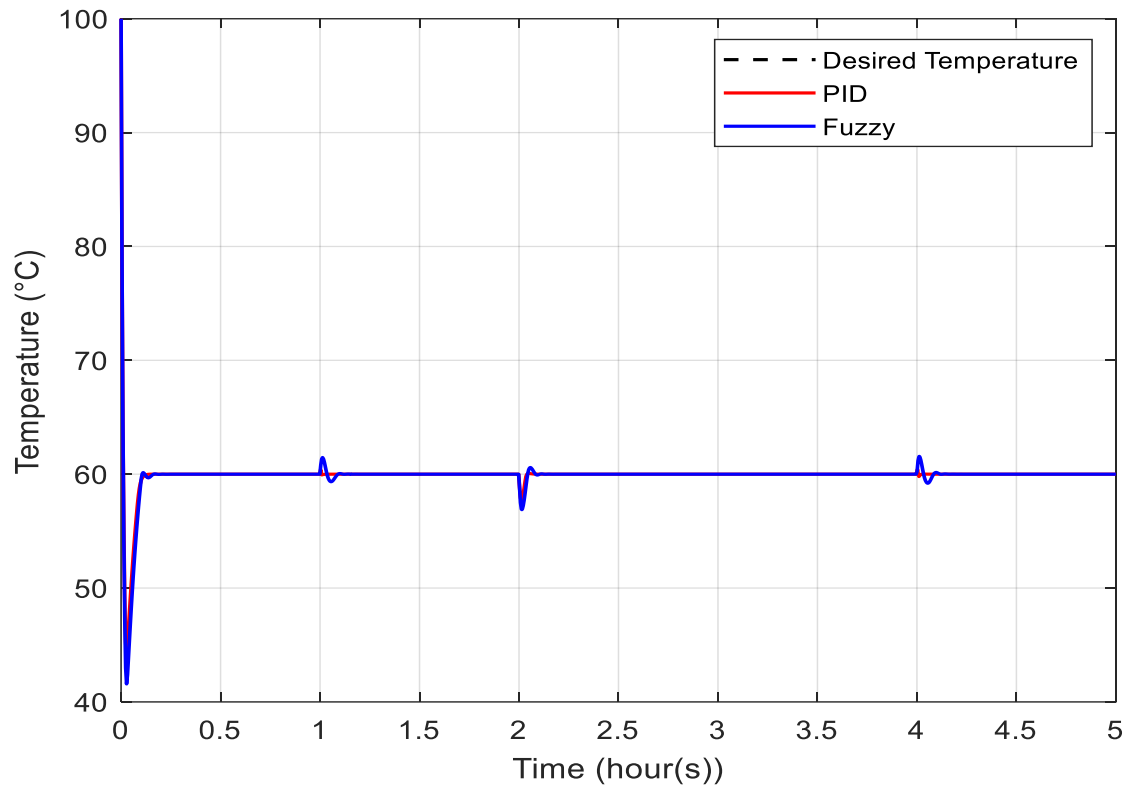


Figure 5.19: Hot fluid outlet temperature under varying mass flow rate

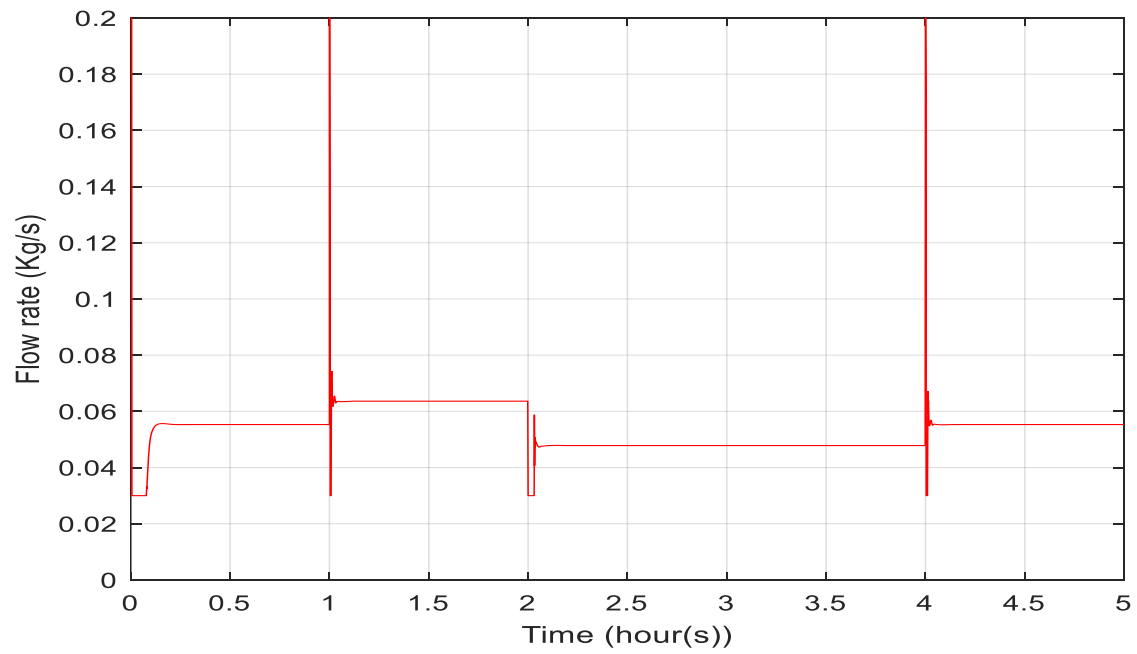


Figure 5.20: Cold fluid mass flow rate under varying hot fluid mass flow rate (PID)

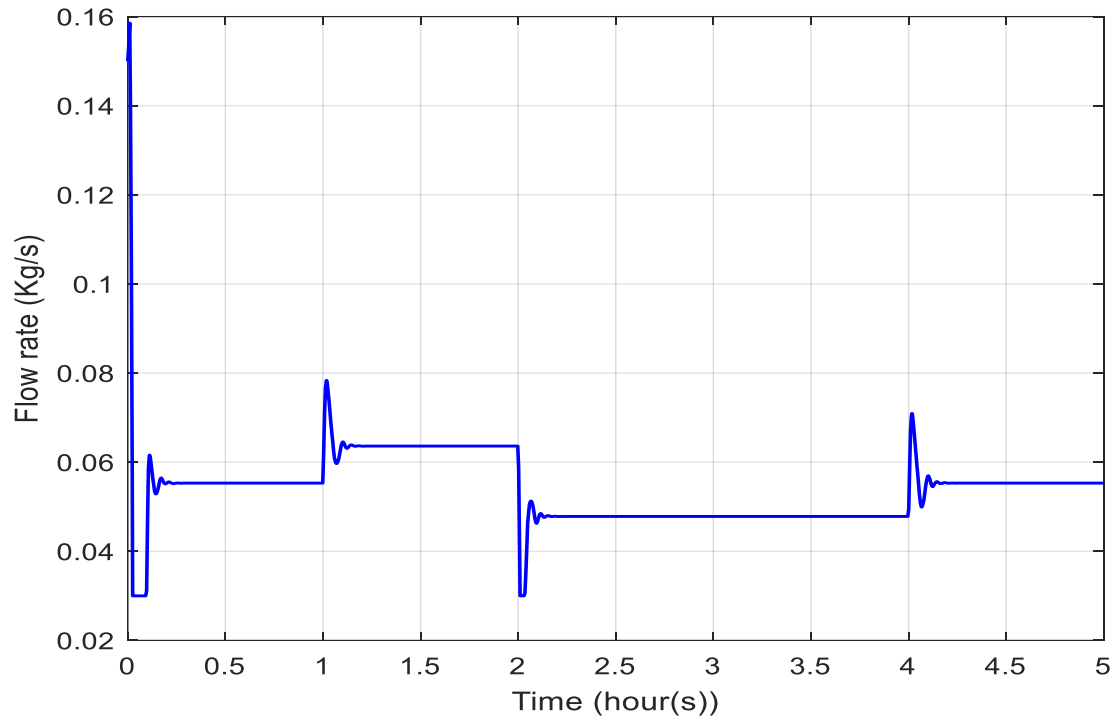


Figure 5. 21: Cold fluid mass flow rate under varying hot fluid mass flow rate (Fuzzy)

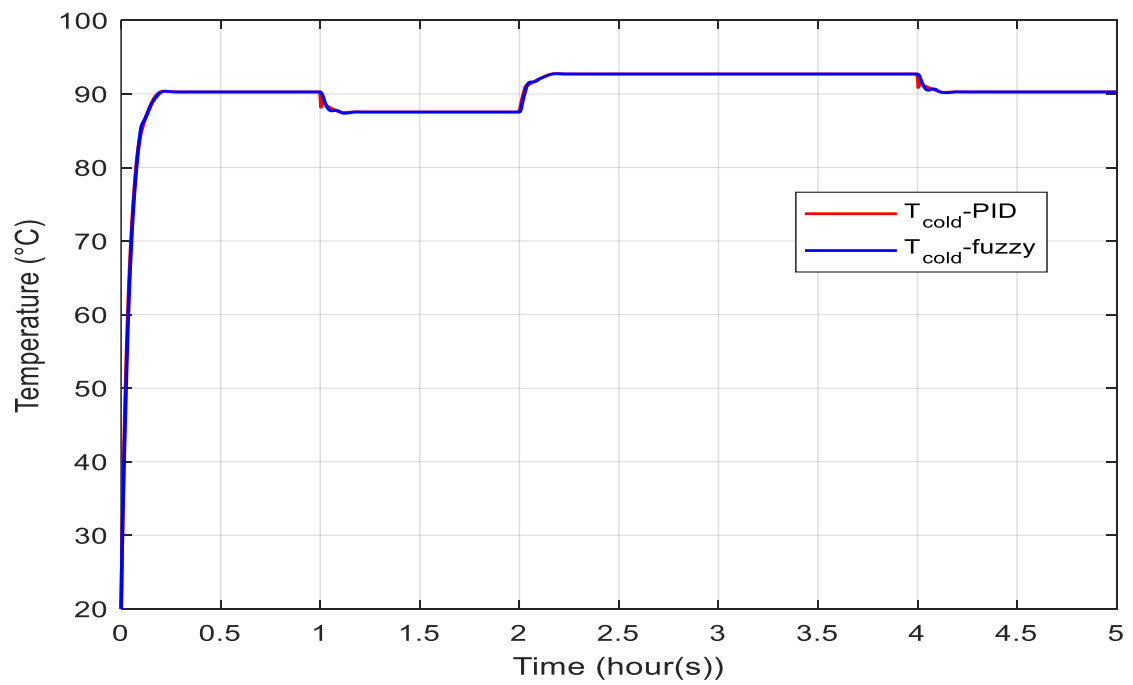


Figure 5. 22: Cold fluid outlet temperature under varying hot fluid mass flow rate

5.4.4 Varying Inlet Temperatures

This scenario investigates the effect of variation of feedback controlled DPHE inlet temperatures on the controller performance. The hot fluid inlet temperature has been altered within the range 95 °C to 105 °C , at the same time the cold fluid inlet temperature has been varied between 17 °C and 23 °C as established in figure 5.23.

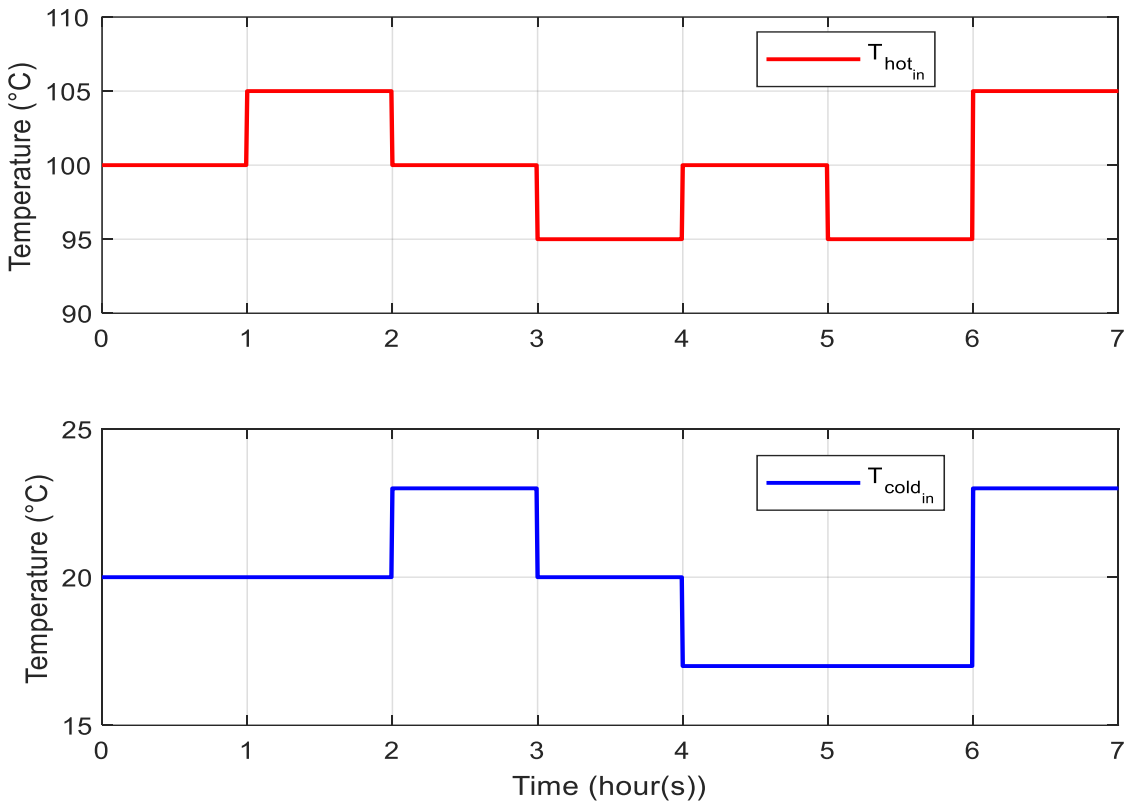


Figure 5. 23: Inlet temperatures

Figure 5.24 shows the response of the inner pipe outlet temperature, where both controllers show an excellent response. Considering ITAE, FLC recorded 475 where PID recorded 36.16. Figures 5.25 and 5.26 depict the mass flow rate obtained from the PID controller and FLC, respectively. The outer pipe outlet temperatures are illustrated in figure 5.27.

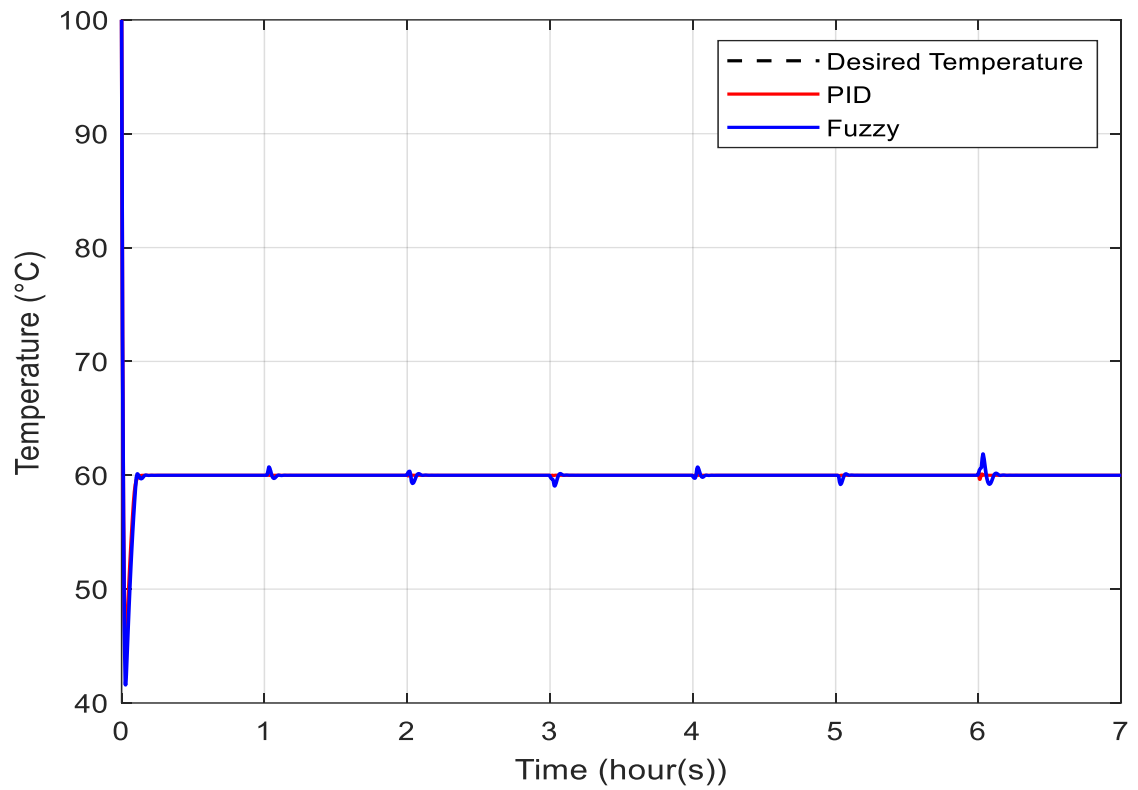


Figure 5. 24: Hot fluid outlet temperature under varying inlet temperatures

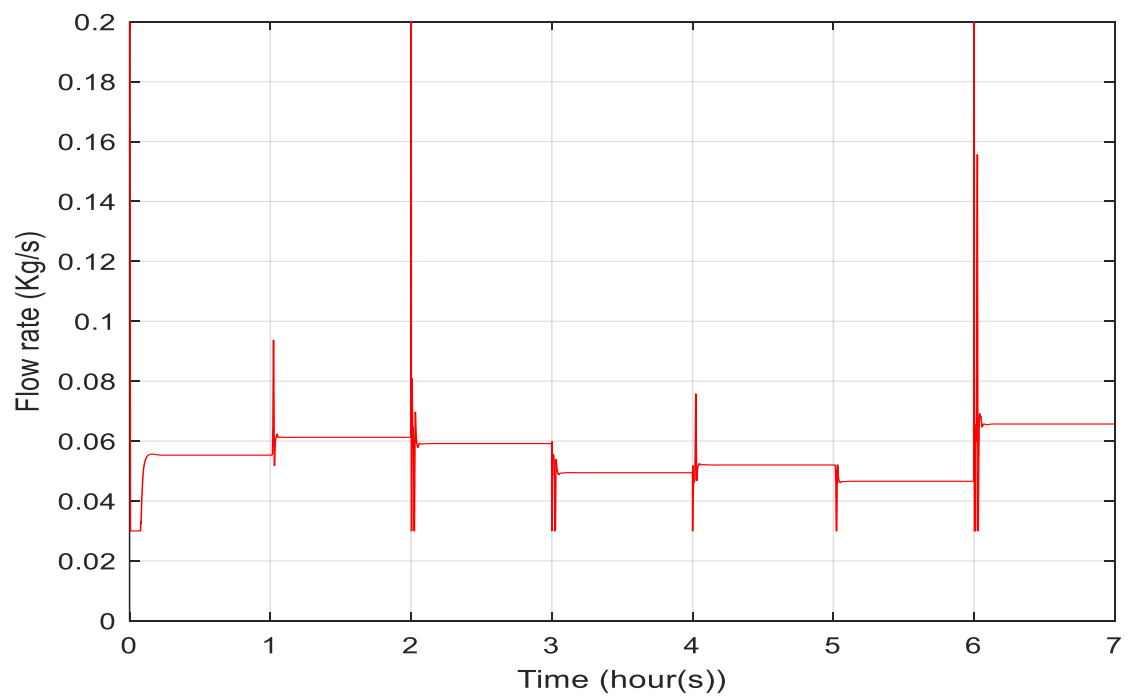


Figure 5. 25: Cold fluid mass flow rate under varying inlet temperatures (PID)

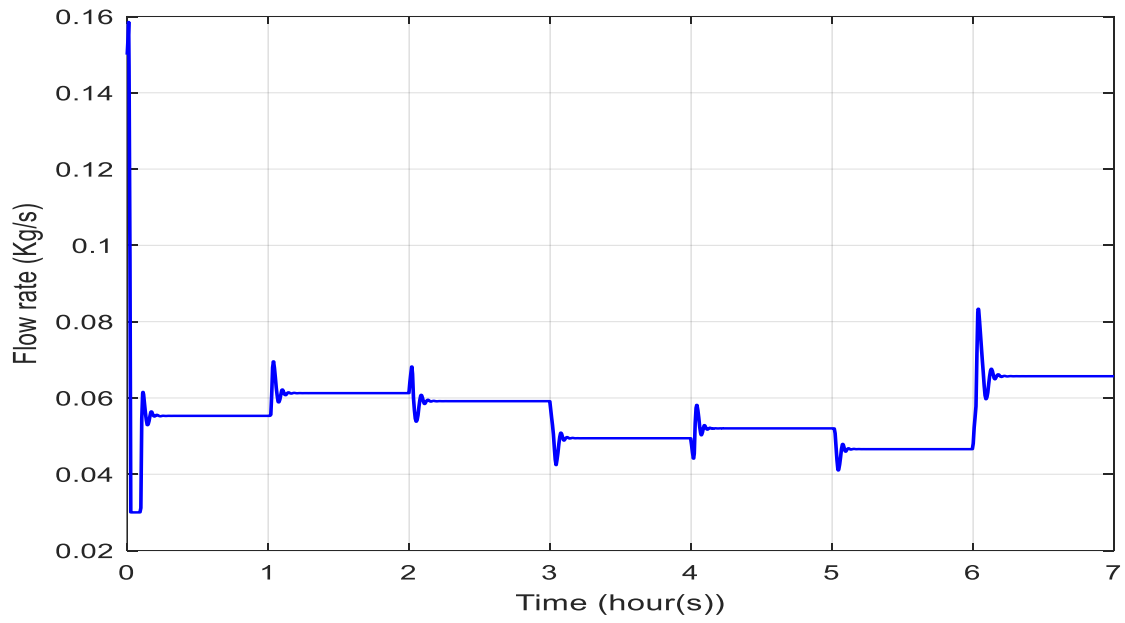


Figure 5. 26: Cold fluid mass flow rate under varying inlet temperatures (fuzzy)

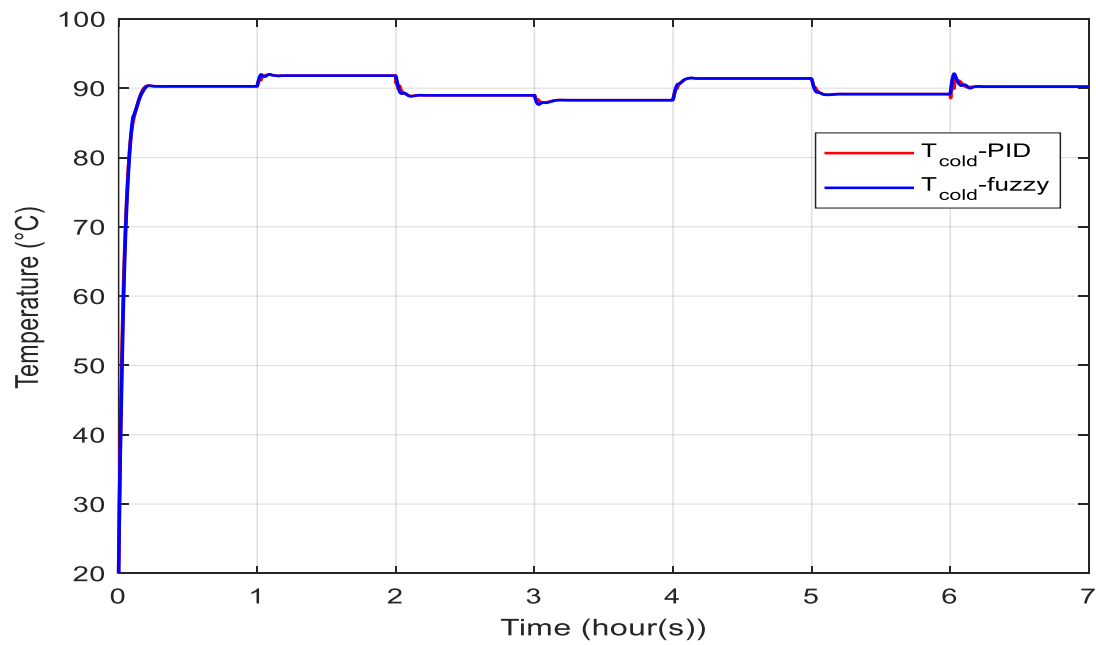


Figure 5. 27: Cold fluid outlet temperature under varying inlet temperatures

5.4.5 Fouling Build-Up

In this scenario, the fouling build-up has been deemed where the fouling resistance is varied, as demonstrated in figure 4.5, to investigate the fouling influence on the FLC and PID controller performance. The build-up of fouling starts after 5 hours and continues until it reaches the peak value at the end of the simulation period, which is equivalent to a reduction in the heat transfer coefficient by 50%. As shown in figure 5.28, both controllers demonstrated excellent regulation capability. The FLC witnessed an ITAE equals 80.9 versus 5.4 for the PID controller.

Figures 5.29 and 5.30 show the cold fluid flow rate attained from the PID controller and FLC, correspondingly, while figure 5.31 depicts the DPHE cold fluid outlet temperature using both PID and FLC.

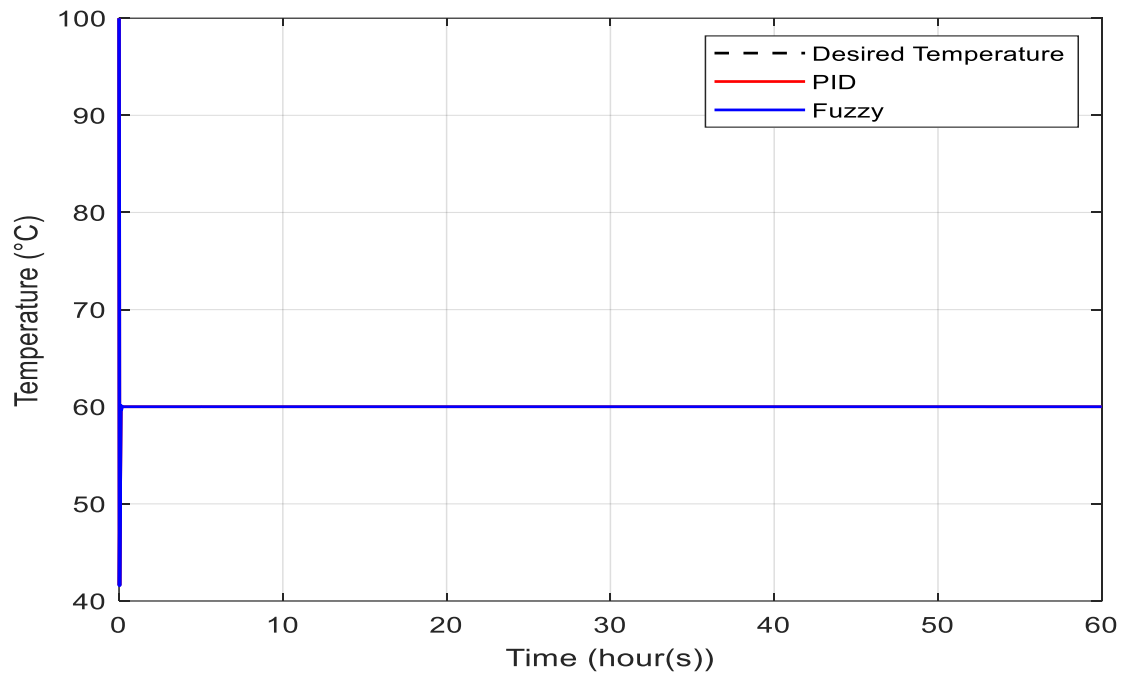


Figure 5. 28: Hot fluid outlet temperature under fouling build-up

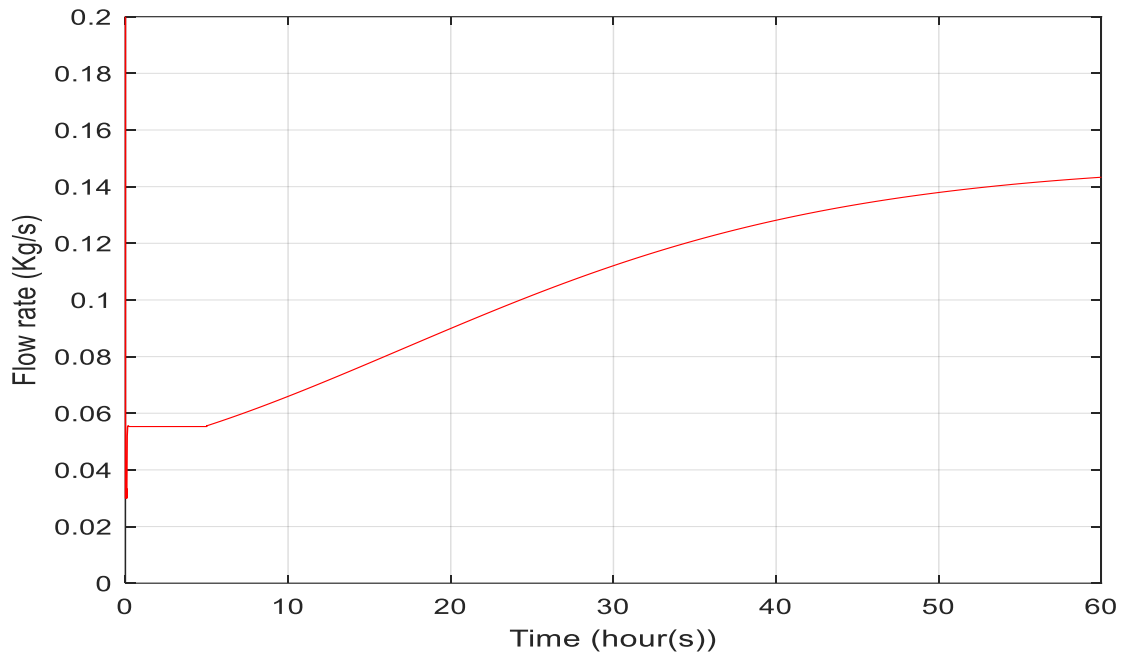


Figure 5. 29: Cold fluid mass flowrate under fouling build-up (PID)

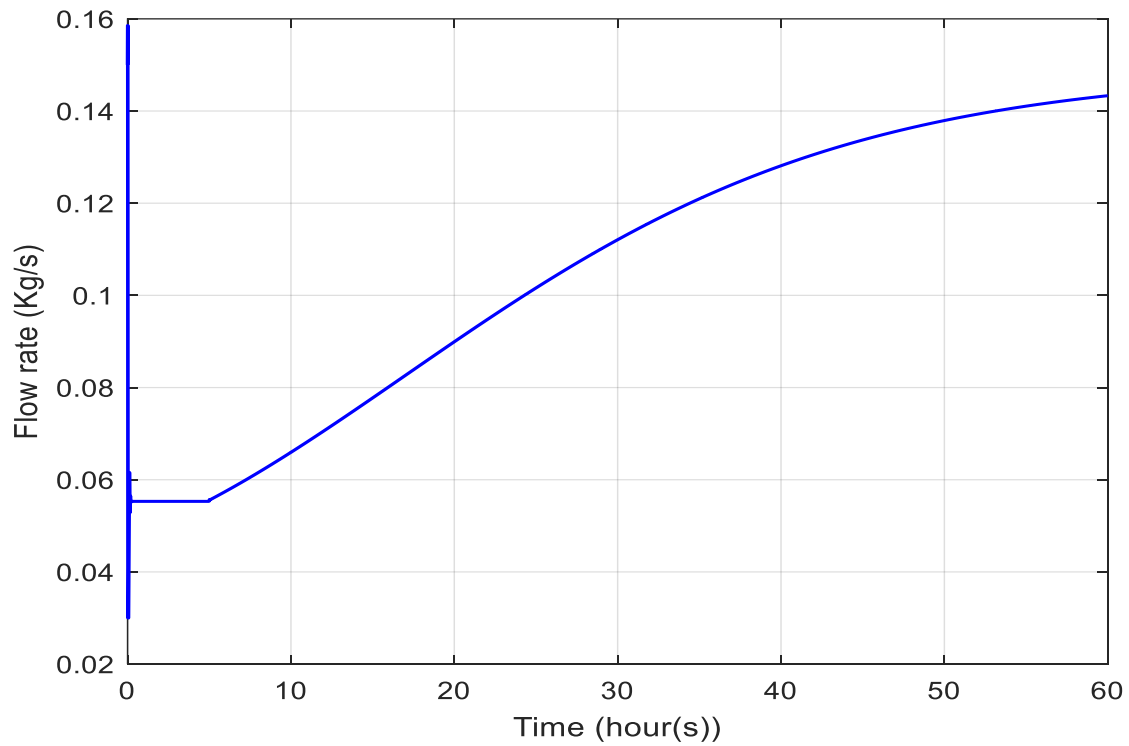


Figure 5. 30: Cold fluid mass flowrate under fouling build-up (Fuzzy)

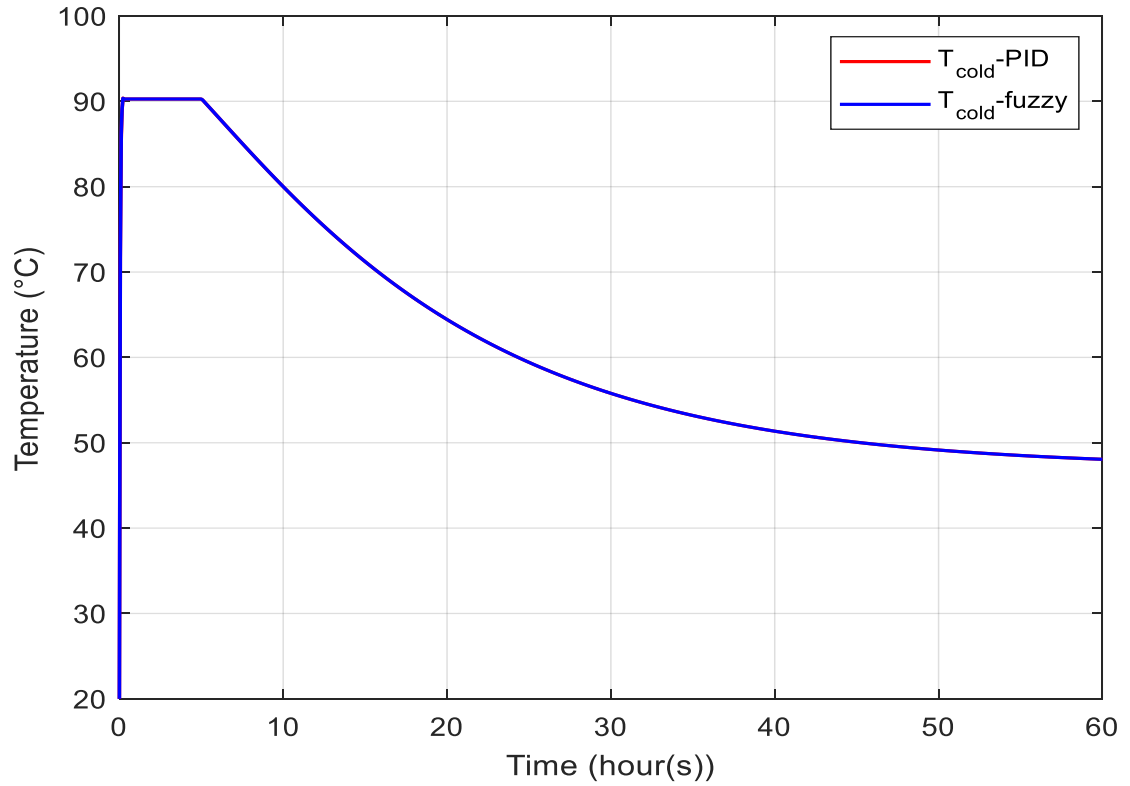


Figure 5. 31: Cold fluid outlet temperature under fouling build-up

5.4.6 Measurement Noise

In this scenario, a band-limited white noise as illustrated in figure 5.32 has been injected into the inner pipe outlet temperature to simulate the measurement noise. as shown in figure 5.33, FLC demonstrated a robust performance against the measurement noise with IATE equals to 1517. In contrast, the PID showed a remarkable deterioration in its performance due to the presence of measurement noise where it recorded IATE equals to 3006. Moreover, The PID controller output experiences a high chattering level as demonstrated in figure 5.34 which can reduce the lifetime of the control element (a valve or a pump). The FLC shows a smooth output as depicted in figure 5.35.

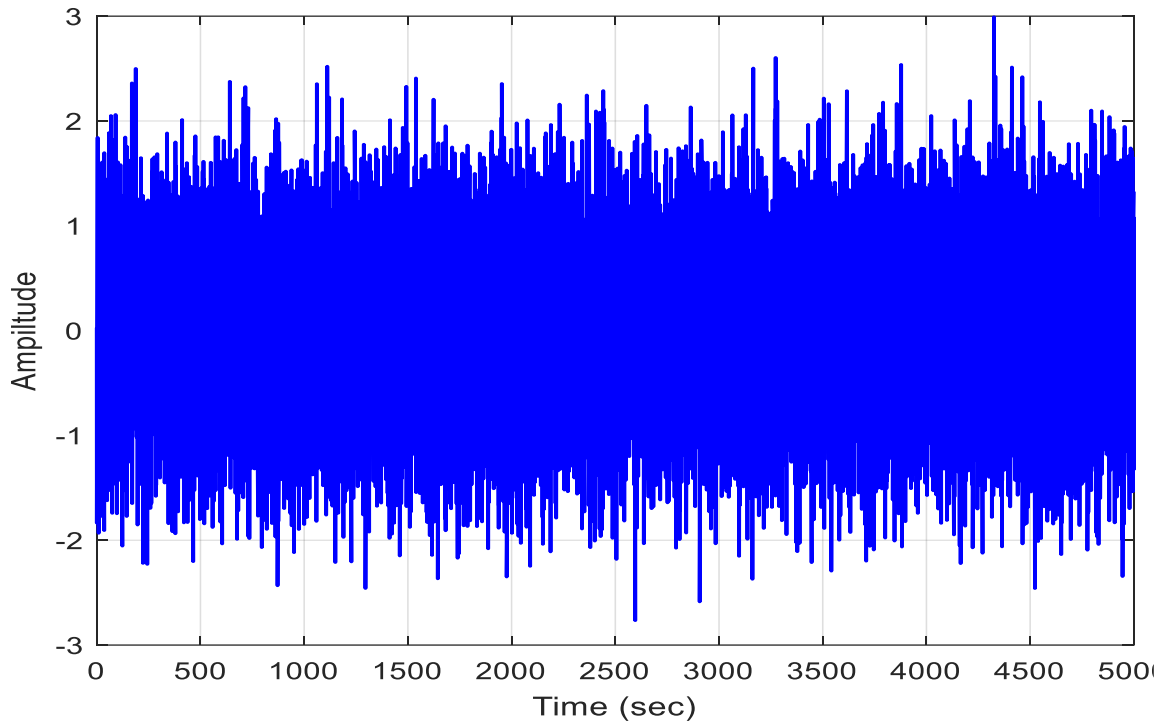


Figure 5.32: injected noise

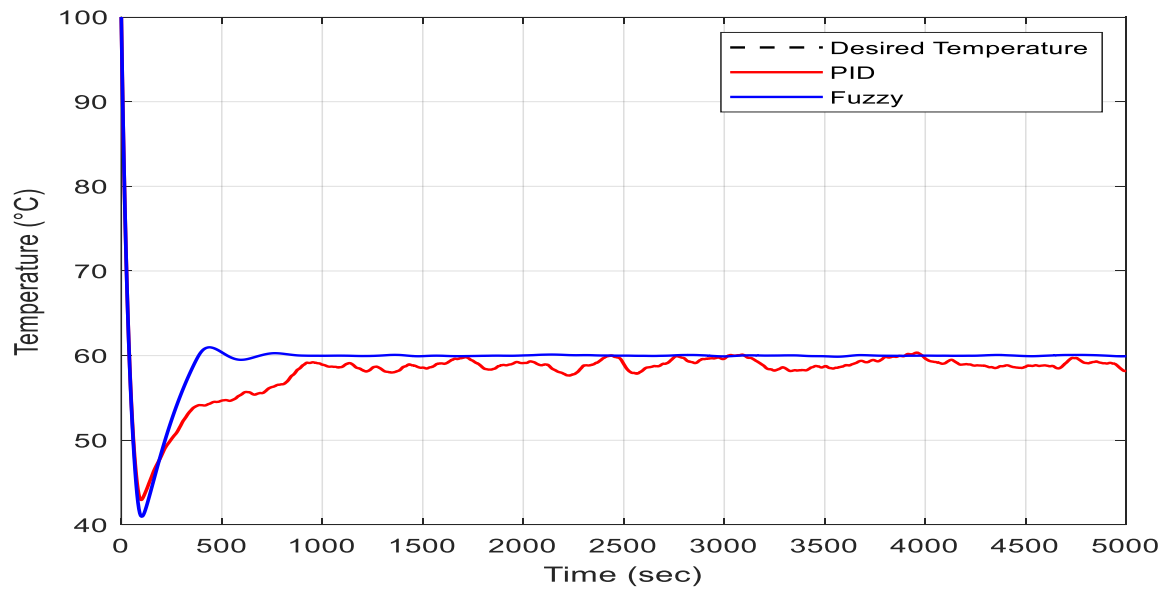


Figure 5.33: Hot fluid outlet temperature under output noise.

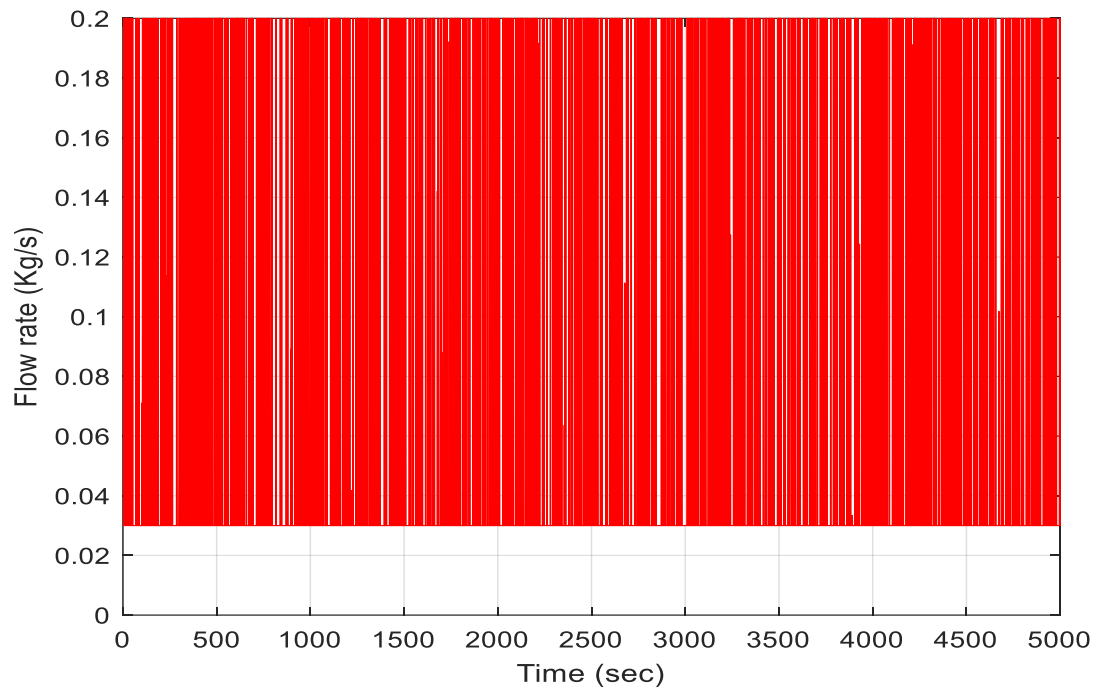


Figure 5. 34: cold fluid mass flow rate under output noise (PID).

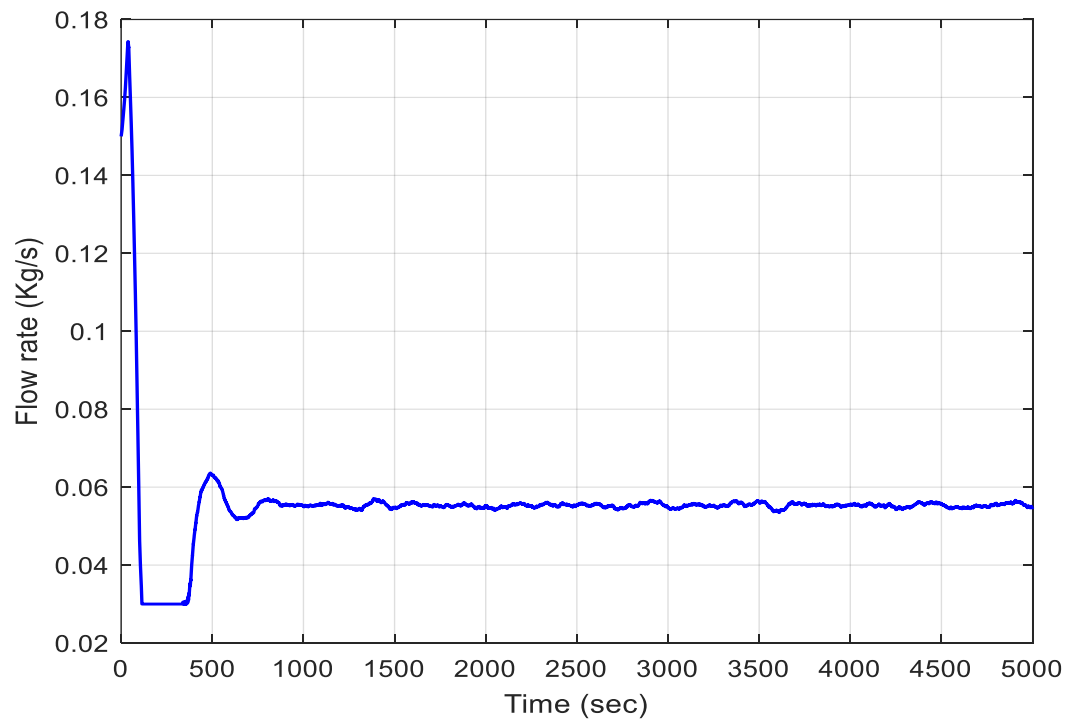


Figure 5. 35: cold fluid mass flow rate under output noise (Fuzzy)

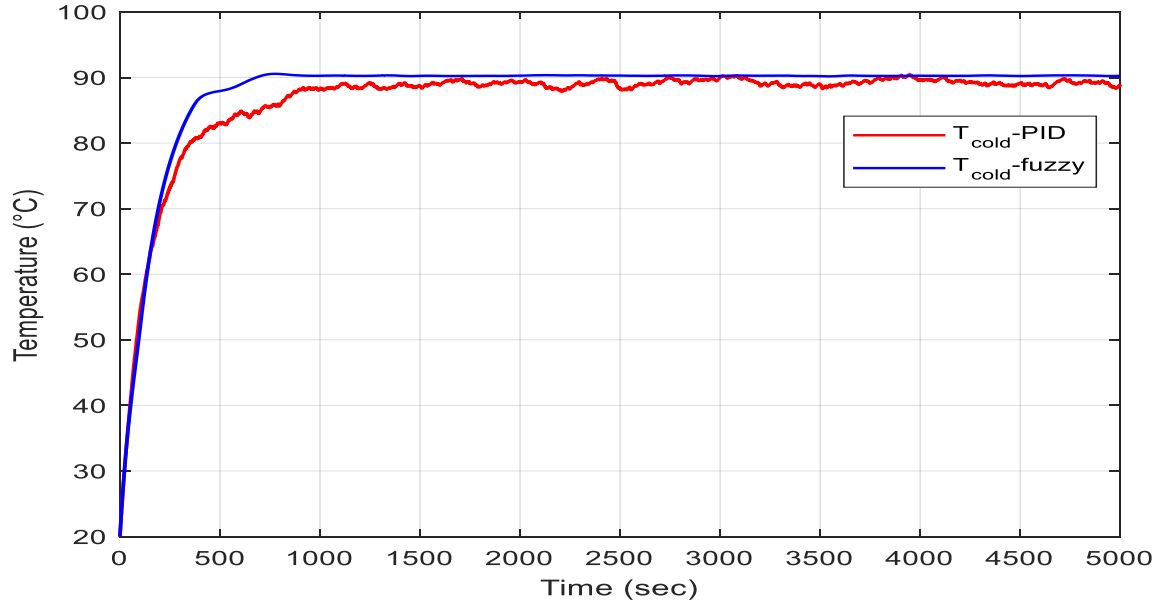


Figure 5. 36: Cold fluid outlet temperature under output noise..

5.5 Concluding Remarks

Two control schemes have been implemented to control the counter flow DPHE. Firstly, a PID controller has been presented where the controller parameters have been optimized using a harmony search metaheuristic algorithm. Then a fuzzy logic controller has been implemented to manipulate the rate of change in the mass flow rate of the outer pipe (cold) fluid. Six scenarios have been considered to evaluate both controllers where PID showed a better performance in terms of ITAE in the first five scenarios. However, considering the measurement noise as illustrated in the last scenario FLC shows superior performance and robustness.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

A numerical model has been developed for the double pipe heat exchanger considering both thermal and hydraulic characteristics as well as modelling the fouling build-up effect on the heat exchanger where a single-phase flow regime is assumed.

Data-driven models for fouling estimation and prediction are developed. A feedforward neural network has been employed for fouling estimation, while a long short-term memory (LSTM) neural network has been deployed for fouling prediction. The estimation model requires only the measurements of pressure drop beside the inner and outer tube outlet temperatures. The training and validation data for the estimation model are obtained from the numerical simulation of the DPHE model, considering a counter flow arrangement, where an asymptotic fouling regime was assumed. Given the historical values of the estimated fouling, an LSTM based prediction model can predict the future trend of the fouling build-up. Both estimation and prediction models showed excellent performance in this case study.

Two control schemes have been considered for fouling compensation. Firstly, a PID controller optimized using harmony search metaheuristic algorithm has been realized to control the inner pipe (hot) fluid outlet temperature of a counter-flow heat exchanger undergoing fouling. A fuzzy logic controller has been implemented for the same objective by manipulating the rate of change in the mass flow rate of the outer pipe (cold) fluid. Both controllers showed excellent performance in terms of compensating the fouling build effect

on the controlled temperature. However, the FLC demonstrated better performance when the process variable measurement noise is considered.

6.2 Future Work

1. Extend the study to address heat exchangers that experience a multi-phase flow.
2. Investigate fouling estimation and compensation for other heat exchangers types.
3. Investigate the possibility of detecting fouling location in heat exchanger networks.

References

- [1] R. J. Brogan, "HEAT EXCHANGERS," in *A-to-Z Guide to Thermodynamics, Heat and Mass Transfer, and Fluids Engineering*, Begellhouse.
- [2] K. Thulukkanam, "Heat Exchanger Design Handbook," *Heat Exch. Des. Handb.*, 2013.
- [3] T. R. Bott, *Fouling of Heat Exchangers*. 1995.
- [4] S. K. Ogbonnaya and O. O. Ajayi, "Fouling phenomenon and its effect on heat exchanger: A review," *Front. Heat Mass Transf.*, vol. 9, 2017.
- [5] D. Q. Kern and R. E. Seaton, "A theoretical analysis of thermal surface fouling.pdf," *Br. Chem. Eng.*, vol. 4, no. 5, pp. 258–262, 1959.
- [6] C. Borges De Carvalho, E. P. Carvalho, and M. A. S. S. Ravagnani, "Dynamic Analysis of Fouling Buildup in Heat Exchangers Designed According to TEMA Standards," *Ind. Eng. Chem. Res.*, vol. 57, no. 10, pp. 3753–3764, 2018.
- [7] S. K. Ogbonnaya and O. O. Ajayi, "Fouling phenomenon and its effect on heat exchanger: A review," *Front. Heat Mass Transf.*, vol. 9, 2017.
- [8] Y. Wang, Z. Yuan, Y. Liang, Y. Xie, X. Chen, and X. Li, "A review of experimental measurement and prediction models of crude oil fouling rate in crude refinery preheat trains," *Asia-Pacific J. Chem. Eng.*, vol. 10, no. 4, pp. 607–625, 2015.
- [9] W. Ebert and C. B. Panchal, "Analysis of Exxon crude-oil-slip stream coking data," *Fouling Mitig. Ind. heat Exch.*, pp. 18–23, 1995.
- [10] G. T. Polley, D. I. Wilson, B. L. Yeap, and S. J. Pugh, "Evaluation of laboratory crude oil threshold fouling data for application to refinery pre-heat trains," *Appl. Therm. Eng.*, vol. 22, no. 7, pp. 777–788, 2002.
- [11] M. R. Jafari Nasr and M. Majidi Givi, "Modeling of crude oil fouling in preheat exchangers of refinery distillation units," *Appl. Therm. Eng.*, vol. 26, no. 14–15, pp. 1572–1577, 2006.
- [12] N. Shetty, U. B. Deshannavar, R. Marappagounder, and R. Pendyala, "Improved threshold fouling models for crude oils," *Energy*, vol. 111, pp. 453–467, 2016.
- [13] R. Smith, J. Loyola-Fuentes, and M. Jobson, "Fouling in heat exchanger networks," *Chem. Eng. Trans.*, vol. 61, pp. 1789–1794, 2017.
- [14] M. Markowski, M. Trafczynski, and K. Urbaniec, "Validation of the method for determination of the thermal resistance of fouling in shell and tube heat exchangers," *Energy Convers. Manag.*, vol. 76, pp. 307–313, 2013.
- [15] S. Delrot, K. Busawon, M. Djemai, F. Delmotte, and M. Dambrine, "Fouling detection in heat exchangers," *IFAC Proc. Vol.*, vol. 44, no. 1 PART 1, pp. 13368–13373, 2011.

- [16] G. R. Jonsson, S. Lalot, O. P. Palsson, and B. Desmet, "Use of extended Kalman filtering in detecting fouling in heat exchangers," *Int. J. Heat Mass Transf.*, vol. 50, no. 13–14, pp. 2643–2655, 2007.
- [17] S. Delrot, T. M. Guerra, M. Dambrine, and F. Delmotte, "Fouling detection in a heat exchanger by observer of Takagi-Sugeno type for systems with unknown polynomial inputs," *Eng. Appl. Artif. Intell.*, vol. 25, no. 8, pp. 1558–1566, 2012.
- [18] L. Sun, R. Saqi, and H. Xie, "Research on the fouling prediction of heat exchanger based on wavelet relevance vector machine," *Lect. Notes Electr. Eng.*, vol. 67 LNEE, pp. 37–45, 2010.
- [19] D. Dragan, "Fault detection of an industrial heat-exchanger: A model-based approach," *Stroj. Vestnik/Journal Mech. Eng.*, vol. 57, no. 6, pp. 477–484, 2011.
- [20] O. Gudmundsson, "Detection of Fouling in Heat Exchangers using Model Comparison," University of Iceland, 2015.
- [21] Ó. Andrjesdóttir, H. Pálsson, S. Lalot, and B. Desmet, "Detection of fouling in a heat exchanger by application of a lock-in technique," *Heat Exch. Fouling Clean. IX*, pp. 373–379, 2011.
- [22] S. Lalot and B. Desmet, "The lock-in technique applied to heat exchangers: A semi-analytical approach and its application to fouling detection," *Appl. Therm. Eng.*, vol. 114, pp. 154–162, 2017.
- [23] F. Coletti and S. MacChietto, "A dynamic, distributed model of shell-and-tube heat exchangers undergoing crude oil fouling," *Ind. Eng. Chem. Res.*, vol. 50, no. 8, pp. 4515–4533, 2011.
- [24] W. Al Hadad, V. Schick, and D. Maillet, "Fouling detection in a shell and tube heat exchanger using variation of its thermal impulse responses: Methodological approach and numerical verification," *Appl. Therm. Eng.*, pp. 612–619, 2019.
- [25] V. R. Radhakrishnan *et al.*, "Heat exchanger fouling model and preventive maintenance scheduling tool," *Fuel*, vol. 86, no. 15, pp. 2383–2388, 2007.
- [26] E. Davoudi and B. Vaferi, "Applying artificial neural networks for systematic estimation of degree of fouling in heat exchangers," *Chem. Eng. Res. Des.*, vol. 130, pp. 138–153, 2018.
- [27] J. Wang, Z. Lv, Y. Liang, L. Deng, and Z. Li, "Fouling resistance prediction based on GA–Elman neural network for circulating cooling water with electromagnetic anti-fouling treatment," *J. Energy Inst.*, 2018.
- [28] M. Trafczynski, M. Markowski, S. Alabrudzinski, and K. Urbaniec, "The influence of fouling on the dynamic behavior of PID-controlled heat exchangers," *Appl. Therm. Eng.*, vol. 109, pp. 727–738, 2016.
- [29] C. Borges De Carvalho, E. P. Carvalho, and M. A. S. S. Ravagnani, "Tuning Strategies for Overcoming Fouling Effects in Proportional Integral Derivative Controlled Heat Exchangers," *Ind. Eng. Chem. Res.*, vol. 57, no. 31, pp. 10518–

10527, 2018.

- [30] J. Oravec, M. Bakošová, M. Trafczynski, A. Vasičkaninová, A. Mészáros, and M. Markowski, “Robust model predictive control and PID control of shell-and-tube heat exchangers,” *Energy*, vol. 159, pp. 1–10, 2018.
- [31] M. Trafczynski, M. Markowski, P. Kisielewski, K. Urbaniec, and J. Wernik, “A modeling framework to investigate the influence of fouling on the dynamic characteristics of PID-controlled heat exchangers and their networks,” *Appl. Sci.*, vol. 9, no. 5, 2019.
- [32] M. Trafczynski, M. Markowski, and K. Urbaniec, “Energy saving potential of a simple control strategy for heat exchanger network operation under fouling conditions,” *Renew. Sustain. Energy Rev.*, vol. 111, pp. 355–364, 2019.
- [33] M. Omid, M. Farhadi, and M. Jafari, “A comprehensive review on double pipe heat exchangers,” *Appl. Therm. Eng.*, vol. 110, pp. 1075–1090, 2017.
- [34] F. P. Incropera and D. P. DeWitt, *Fundamentals of Heat and Mass Transfer*, Seven Edit. 2011.
- [35] P. J. Pritchard and J. W. Mitchell, *Fox and McDonald’s introduction to fluid mechanics*, 9th Editio. John Wiley & Sons, 2016.
- [36] D. Brkić, “Review of explicit approximations to the Colebrook relation for flow friction,” *J. Pet. Sci. Eng.*, vol. 77, no. 1, pp. 34–48, 2011.
- [37] L. C. Thomas, *Heat transfer--professional version*, Second. Capstone publishing corporation, 1999.
- [38] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. E. Mohamed, and H. Arshad, “State-of-the-art in artificial neural network applications: A survey,” *Heliyon*, vol. 4, no. 11, 2018.
- [39] S. Haykin, *Neural Networks and Learning Machines*, vol. 3. Pearson Prentice Hall New Jersey, 2008.
- [40] M. Gopal, *Applied Machine Learning*. McGraw-Hill Education, 2018.
- [41] M. Z. Alom *et al.*, “A state-of-the-art survey on deep learning theory and architectures,” *Electron.*, vol. 8, no. 3, 2019.
- [42] M. Abdel-Nasser and K. Mahmoud, “Accurate photovoltaic power forecasting models using deep LSTM-RNN,” *Neural Comput. Appl.*, pp. 1–14, 2017.
- [43] C. Wang, S. Fu, Z. Xiao, M. Tang, and D. Liu, “Long Short-Term Memory Neural Network (LSTM-NN) Enabled Accurate Optical Signal-to-Noise Ratio (OSNR) Monitoring,” *J. Light. Technol.*, vol. 37, no. 16, pp. 4140–4146, 2019.
- [44] K. H. Ang, G. Chong, and Y. Li, “PID control system analysis, design, and technology,” *IEEE Trans. Control Syst. Technol.*, vol. 13, no. 4, pp. 559–576, 2005.

- [45] K. Ogata and Y. Yang, *Modern control engineering*, 5th ed., vol. 5. Prentice hall Upper Saddle River, NJ, 2010.
- [46] E. M. Shaban, H. Sayed, and A. Abdelhamid, "A novel discrete PID+ controller applied to higher order/time delayed nonlinear systems with practical implementation," *Int. J. Dyn. Control*, vol. 7, no. 3, pp. 888–900, 2019.
- [47] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A New Heuristic Optimization Algorithm: Harmony Search," *Simulation*, vol. 76, no. 2, pp. 60–68, 2001.
- [48] Z. Geem, *Music-Inspired Harmony Search Algorithm*, vol. 191, no. 1. 2009.
- [49] T. Zhang and Z. W. Geem, "Review of harmony search with respect to algorithm structure," *Swarm Evol. Comput.*, vol. 48, pp. 31–43, 2019.
- [50] K. S. Lee and Z. W. Geem, "A new meta-heuristic algorithm for continuous engineering optimization: Harmony search theory and practice," *Comput. Methods Appl. Mech. Eng.*, vol. 194, no. 36–38, pp. 3902–3933, 2005.
- [51] Y. Cheng, Y. M., Li, L., Lansivaara, T., Chi, S. C., & Sun, "An improved harmony search minimization algorithm using different slip surface generation methods for slope stability analysis," *Eng. Optim.*, vol. 40, no. 2, pp. 95–115, 2008.
- [52] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Appl. Math. Comput.*, vol. 188, no. 2, pp. 1567–1579, 2007.
- [53] K. M. Passino and S. Yurkovich, *Fuzzy control*. 2010.
- [54] K. Premkumar and B. V. Manikandan, "Bat algorithm optimized fuzzy PD based speed controller for brushless direct current motor," *Eng. Sci. Technol. an Int. J.*, vol. 19, no. 2, pp. 818–840, 2016.

Vitae

Name	Mohammed Ahmed Mohammed Eltoum Mohammed ALi
Nationality	Sudanese
Date of Birth	06-October-1993
Email	m-dm@live.com
Address	East Nile, Khartoum 11111, Sudan
Academic Background	B.Eng Electrical Engineering, Sudan University of Science and Technology, Khartoum, Sudan. M.Sc Systems and Control Engineering, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.