MODELLING AND CONTROL OF SUBMERGED MEMBRANE BIOREACTOR FILTRATION PROCESS USING NEURAL NETWORK MODEL PREDICTIVE CONTROL

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A thesis submitted in fulfillment of the
requirements for the award of the degree of
Doctor of Philosophy (Electrical Engineering)

Faculty of Electrical Engineering
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JULY 2018

To my beloved parents Yusuf and Kasih

To my wife Nazurah, my children Muhammad Hafiy, Muhammad Faheem, Muhammad Aathif & Yusra

ACKNOWLEDGEMENT

First and foremost, I would like to praise to Almighty Allah for giving me strength and ability to endure the hard times I have been through and through. Without Him, I am sure I would not be able to complete my research journey.

I would like to extend my deepest appreciation and gratitude to my supervisor Assoc. Prof. Ir. Dr. Norhaliza Abdul Wahab for her continuous supports, invaluable guidance and countless moments of attention that she had generously spared throughout this research. I am also particularly thankful to my co-supervisor Dr. Shafishuhaza Sahlan for her contributions and support in this research work.

My special thanks go to my beloved parents for their endless encouragement and prayers especially throughout the PhD journey. To my wife and my children, thank you very much for all the encouragement, understanding and sacrifices.

My gratitude also goes to Prof. Dr. Ahmad Fauzi Ismail, Mr. Ng Bee Cher and Mr Suhaimi from Advance Membrane Technology Center (AMTEC-UTM) for the advice on the plant development and research. I also thank the Process Control Lab members that helpdirectly or indirectly toward completion of this research.

Lastly, but not the least, I would like to convey my utmost gratitude and appreciation to Universiti Teknologi MARA (UiTM) and Ministry of Higher Education for giving me the opportunity to pursue my PhD studies in Universiti Teknologi Malaysia (UTM) under young lecture scholarship.

ABSTRACT

Membrane bioreactor employs an efficient filtration technology for solid and liquid separation in wastewater treatment process. Development of membrane filtration model is significant as this model can be used to predict fouling development which is later utilized in control development. Most of the available models only suitable for monitoring purpose, which are too complex, required many variables and not suitable for control system design. Artificial neural network (ANN) is a simple and efficient method in modelling of filtration process. In this thesis, the dynamic ANN is used to model the filtration process using the developed submerged membrane bioreactor (SMBR) pilot plant. The accuracy of the dynamic neural network is further improved using the proposed optimization algorithms. These algorithms are developed based on the hybrid particle swarm optimization and gravitational search algorithm (PSOGSA) using cooperative approach. The first cooperative PSOGSA (CPSOGSA-1) is developed using master-slave cooperative technique where one master group and a few slave groups are created. The second cooperative PSOGSA (CPSOGSA-2) is where multiple groups are created, and the best solution found by one of the group will share with other groups. The model performances of the ANN training and testing are assessed using mean square error, mean absolute deviation and correlation coefficient. To establish the model training performance, another set of input output data from heating process is performed. Furthermore, the training performance of the algorithms is tested to minimize ten mathematical functions. The simulation results indicate the proposed algorithms outperformed the existing PSO, GSA and PSOGSA algorithms for the SMBR model. Similar trends of results can be observed for heating process model and for all benchmark functions tested. An improved SMBR trained model is then used for neural network model predictive control (NNMPC) design for permeate flux control as to prevent flux decline in the membrane filtration cycle due to fouling problem. The PSO, CPSOGSA-1 and CPSOGSA-2 algorithms are utilized in NNMPC real-time optimization cost function. From the experimental result, the best filtration control is given by NNMPC with CPSOGSA-2 algorithm. The superiority of the NNMPC in membrane filtration control resulted from real time implementation showed an improvement of 100% overshoot, 7.06% settling time and 11.96% of integral absolute error when compared to PID-PSO.

ABSTRAK

Bioreaktor membran menggunakan teknologi penapisan yang cekap untuk pemisahan pepejal dan cecair dalam proses rawatan air sisa kumbahan. Pembangunan model penapisan membran penting kerana model ini boleh digunakan untuk meramalkan pembentukkan kotoran yang kemudiannya digunakan dalam membangunkan system kawalan. Kebanyakan model yang ada hanya sesuai digunakan untuk pemantauan kerana ianya terlalu kompleks, memerlukan banyak pembolehubah, dan tidak sesuai untuk reka bentuk sistem kawalan. Rangkaian neural buatan (ANN) adalah satu kaedah yang mudah dan berkesan dalam pemodelan proses penapisan. Dalam tesis ini, ANN digunakan untuk memodelkan proses penapisan menggunakan loji pandu bioreaktor membran tenggelam (SMBR) yang dibangunkan. Ketepatan rangkaian neural yang dinamik terus dipertingkatkan dengan penggunaan algoritma pengoptimuman dicadangkan. Algoritma ini dibangunkan berdasarkan pengoptimuman hibrid zarah kerumunan dan graviti algoritma carian (PSOGSA) menggunakan pendekatan koperasi. Algoritma koperatif PSOGSA pertama (CPSOGSA-1) dibangunkan menggunakan teknik koperatif tuan-hamba di mana satu kumpulan induk dan beberapa kumpulan hamba yang dicipta. Algoritma koperatif kedua PSOGSA (CPSOGSA-2) adalah di mana beberapa kumpulan dicipta, dan penyelesaian terbaik yang ditemui oleh salah satu kumpulan yang akan berkongsi dengan kumpulan lain. Persembahan latihan and ujian model ANN dinilai menggunakan ralat persegi min, sisihan min mutlak dan pekali korelasi. Untuk mewujudkan prestasi latihan model, satu lagi set data output input dari proses pemanasan dilakukan. Tambahan pula, prestasi latihan algoritma diuji untuk mengurangkan sepuluh fungsi matematik. Keputusan simulasi menunjukkan algoritma yang dicadangkan mengatasi PSO, GSA dan PSOGSA algoritma yang sedia ada bagi model SMBR itu. Trend yang sama keputusan boleh diperhatikan bagi model proses pemanasan dan untuk semua fungsi penanda aras diuji. Model SMBR terlatih yang terbaik kemudiannya digunakan untuk model rangkaian neural kawalan ramalan (NNMPC) yang reka bentuk untuk kawalan fluks meresap untuk mengelakkan penurunan fluks dalam kitaran penapisan membran kerana masalah kotoran. Algoritma PSO, CPSOGSA-1 dan CPSOGSA-2 digunakan dalam NNMPC fungsi kos pengoptimuman masa nyata. Dari hasil eksperimen, kawalan penapisan terbaik diberikan oleh NNMPC dengan algoritma CPSOGSA-2. Keunggulan NNMPC dalam kawalan penapisan membran hasil daripada pelaksanaan masa nyata menunjukkan peningkatan sebanyak 100% terlajak, 7.06% masa pengenapan dan 11.96% bagi ralat mutlak kamiran berbanding PID-PSO.

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LIST OF ABBREVATIONS

ABC	-	Artificial Bee Colony
ANN	-	Artificial Neural Network
BOD	-	Biological oxygen demand
COD	-	Chemical oxygen demand
CPSOGSA-1	-	Cooperative PSOGSA algorithm 1
CPSOGSA-2	-	Cooperative PSOGSA algorithm 2
GA	-	Genetic Algorithm
GSA	-	Gravitational Search Algorithm
IAE	-	Integral Absolute Error
MAD	-	Mean Absolute Deviation
MBR	-	Membrane Bioreactor
MPC		Model Predictive Control
MSE	-	Mean Square Error
NN	-	Neural Network
NNMPC		Neural Network Model Predictive Control
NNMPC-PSO	-	NNMPC With PSO
NNMPC-PSO(1)	-	NNMPC With PSO (Prediction Horizon=15, Control
	-	Horizon = 10)
NNMPC-PSO(2)	-	NNMPC With PSO (Prediction Horizon=10, Control
	-	Horizon = 7)
NNMPC-PSO(3)	-	NNMPC With PSO (Prediction Horizon=15, Control
	-	Horizon = 10)
NNMPC-PSO(4)	-	NNMPC With PSO (Prediction Horizon=5, Control
	-	Horizon = 3)
NNMPC-PSO(5)	-	NNMPC With PSO (Prediction Horizon=5, Control

	-	Horizon = 2)
NNMPC-CPSOGSA-1	-	NNMPC With CPSOGSA-1
NNMPC-CPSOGSA-1(1)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=15, Horizon = 10)
NNMPC-CPSOGSA-1(2)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=10, Control Horizon = 7)
NNMPC-CPSOGSA-1(3)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=10, Control Horizon = 5)
NNMPC-CPSOGSA-1(4)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=5, Control Horizon = 3)
NNMPC-CPSOGSA-1(5)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=5, Control Horizon = 2)
NNMPC-CPSOGSA-2	-	NNMPC With CPSOGSA-2
NNMPC-CPSOGSA-2(1)	-	NNMPC With CPSOGSA-1 (Prediction Horizon=15, Horizon = 10)
NNMPC-CPSOGSA-2(2)	-	NNMPC With CPSOGSA-2 (Prediction Horizon=10, Control Horizon = 7)
NNMPC-CPSOGSA-2(3)	-	NNMPC With CPSOGSA-2 (Prediction Horizon=10, Control Horizon = 5)
NNMPC-CPSOGSA-2(4)	-	NNMPC With CPSOGSA-2 (Prediction Horizon=10, Control Horizon = 5)
NNMPC-CPSOGSA-2(5)	-	NNMPC With CPSOGSA-2 (Prediction Horizon=10, Control Horizon = 5)
PID	-	Proportional Integral Derivative
POME		Palm Oil Mill Effluent
PSO	-	Particle Swarm Optimization
PSOGSA		Hybrid PSO and GSA
RTO	-	Real Time Optimization
SMBR		Submerged Membrane Bioreactor
TMP	-	Transmembrane Pressure
		Ultrafiltration

LIST OF SYMBOLS

ΔT	-	Filtration duration
J_f	-	Filtration flux
J_b	-	Backwash flux
t_f	-	Filtration time
t_b	-	Backwash time
t_r	-	Relaxation time
J	-	Flux
ΔP	-	TMP different
R_T	-	Total resistance
w_{ij}	-	Network weight
w_{i0}	-	Network bias
f_i	-	Activation function
x_i	-	GSA agent
N	-	Agent dimension
M_{aj}	-	Gravitational mass
$G(t)$	-	Gravitational constant
F	-	Gravitational force
$R_{ij}(t)$	-	Euclidean distance between x_i and x_j
$rand$	-	Random number [0 1]
M_{ij}	-	Initial mass
$best\ (t)$	-	Best performance
$worst\ (t)$	-	Worst performance
V_i	-	Agent velocity
a_i	-	Acceleration constant

X_i	-	Agent position
f_i	-	Fitness value
V_{id}	-	Particle velocity
X_{id}	-	Particle position
C	-	Constant
w	-	Inertia weight
w_{max}	-	Maximum inertia weight
w_{min}	-	Minimum inertia weight
$pBest$	-	Personal best
$gBest$	-	Global best
V_H	-	PSOGSA agent velocity
X_H	-	PSOGSA agent position
$J(H_p, H_c)$	-	MPC cost function
H_p	-	Prediction horizon
H_c	-	Control horizon
r	-	Reference
φ	-	Weight matrix
μ	-	Weight matrix
u	-	Input
Δu	-	Change of input
y	-	Output
$\hat{y}$	-	Prediction output
$t_{relexation}$	-	Relaxation time
$t_{permeate}$	-	Permeate time
z^{-1}	-	Delay operator
MSE_{flux}	-	Mean square error flux
MSE_{TMP}	-	Mean square error TMP
x_i	-	Measured value
$\bar{x}$	-	Mean of the measured value
y_i	-	Predicted value
$\bar{y}$	-	Mean of the predicted value

R	-	Correlation coefficient
V_M	-	CPSOGSA-1 master particle velocity
X_M	-	CPSOGSA-1 master particle position
V_l	-	CPSOGSA-2 particle velocity
X_l	-	CPSOGSA-2 particle position
δ	-	CPSOGS-2 cooperative coefficient group 1
γ	-	CPSOGS-2 cooperative coefficient group 2
λ	-	CPSOGS-2 cooperative coefficient group 3
$e(t)$	-	Error
K_p	-	Proportional gain
K_i	-	Integral gain
K_d	-	Derivative gain
K_c	-	Process gain
T_i	-	Time constant
T_d	-	Time delay
y_{flux}	-	Flux output
y_{TMP}	-	TMP output

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CHAPTER 1

INTRODUCTION

1.1 Background

High concern in water and wastewater treatment quality has trigged more research on the treatment technology. Membrane bioreactor (MBR) was recognized as a promising technology to replace conventional activated sludge (CAS) process. This technology has proven to be very useful for wastewater treatment in producing high-quality effluent (treated water) either from industrial or domestic waste. Among the well-known capability of the MBR system are efficient organics removal, enhanced nutrient removal stability, lower sludge production, smaller footprint, effluent disinfection and high loading rate capabilities.

MBR is the combination of biological process in a bioreactor and membrane filtration process. Unlike the CAS configuration, the MBR does not have standard stages of the process. Some of the MBR plants were developed from the combination of CAS and membrane filtration to replace secondary settler of the treatment. The MBR systems also can be built with more simplified configuration of it nitrification and denitrification process, where some of the configuration of the MBR system is only design with a single bioreactor and this plant is running similar principle with sequential bioreactor (SBR) system [1]. With this configuration, the size of the treatment plant is much smaller compared to the conventional system.

Membrane filtration process is a crucial element in any MBR plant. Application of membrane technology in filtration system is the approach where the membrane that produces from polymers used as a filtering mechanism to separate the effluent from the biomass. The application of membrane filtration on MBR system is to provide better solid-liquid separation in wastewater treatment process. The membrane will filter the unwanted solid material from the effluent discharged. Several techniques in membrane filtration process such as microfiltration (MF), ultrafiltration (UF), nanofiltration and reverse osmosis (RO) have been applied in water and wastewater treatment industries [2].

Membrane fouling is a major problem in membrane filtration process, if not carefully handle it will lead to the high operating cost and low filtration output (permeate flux). Fouling in membrane filtration can cause high energy consumption on pumping, cleaning and expensive membrane replacement cost[3][4][5].

In any MBR system, membrane filtration plays most important role in the treatment process where this system usually placed at the final stage of the treatment. Membrane technology in filtration system is the approach where the membrane that produces from polymers used as a filtering mechanism to separate the effluent from the biomass. As a result, the effluent quality is significantly higher than that generated by conventional treatment. Thus, there is no need for a further tertiary disinfection process.

Due to its effectiveness in producing high quality of effluent, MBR is getting a lot of attention around the world. Investments in this technology are exponential increase each year which indicate MBR will be the future superior technology for wastewater treatment. Due to this rapid development of MBR application in the world, it is important to gain a better understanding of its operations regarding parameters that affect the process performance, especially the operating parameters. Finally, with the sufficient knowledge of the MBR system, the process can be adequately controlled and optimized.

1.2 Problem Statement

Despite many advantages of MBR, the system also has its difficult part. The main issue with the MBR is the fouling in the filtration process. Fouling can be described as blockage during the membrane filtration process that caused by many factors such as colloidal, particulate, solute materials, plant operations and the characteristics of the membrane [4]. Fouling can cause permeate flux (filtration output) decline in the filtration process or high transmembrane pressure (TMP) measurement [2]. Therefore it is important to provide adequate flux control system to ensure an optimal permeate flux [6][7].

Cleaning sequence in MBR process is among popular techniques used to reduce fouling such as aeration airflow, backwash, relaxation and chemical cleaning [8][9]. Fouling also can be reduced when running below critical flux condition[10][11].To avoid flux decline in the MBR filtration process, a reliable feedback control is needed. The existing PID controller is not capable to produce reliable and efficient control for the SMBR filtration process. The PID controller usually suffer from the high overshoot and required the controller to be re-tuned to get a good performance[12]. Model-based control technique is an alternative to the conventional PID controller to produce better control performance. This method requires an acceptable degree of model accuracy and model reliability to ensure the controller is at the desired performance.

The existing mathematical models for SMBR are too complex involving many parameters and most of the variables need to be tuned. The ANN model is used alternatively to model the MBR process. However, the existing ANN models are developed to monitor the effluent quality and not for the control purpose. In order to perform a model based control, the technique requires more simpler and reliable model. Paul[13] proposed a time series system identification modelling technique using two inputs and one output of the membrane filtration parameter. The filtration models are developed using linear autoregressive with exogenous input (ARX), ARMAX, subspace and state space technique. The important of time series modelling also presented by [14] where the time series analysis can revealed the characteristic of the phenomenon as well as the future prediction of the membrane filtration process. However, the linear time series modelling technique is lack of accuracy and poor prediction[13]. Hence, nonlinear time series neural network modelling is more suitable for the SMBR filtration application.

1.3 Objectives

This research is focusing on the development of submerged membrane filtration model and design of neural network based model based control in submerged membrane bioreactor (SMBR) filtration process. Several objectives set to fulfil the research aim, as follows:

1. Develop and evaluate the SMBR filtration process model using ANN.
2. Design, test and analyze a neural network based model predictive control (NNMPC) for a membrane filtration flux control.
3. Evaluation and performance analysis of the NNMPC for the SMBR filtration process.

1.4 Scope of Study

Based on the objectives of the research this work will cover:

1. Development of filtration model using ANN for SMBR pilot plant.
2. GSA, PSO and PSOGSA are used to train ANN models.
3. Develop a Hybrid PSOGSA algorithms using cooperative approach for ANN model improvement.
4. Evaluate the algorithm using heating process ANN model.
5. Benchmark the algorithms using ten mathematical functions minimization.
6. Develop a neural network-based model predictive control (NNMPC) for permeate flux with proposed cooperative PSOGSA algorithms.

7. Implementation and evaluation of the controller developed in (h) in SMBR pilot plant.
8. Compare the developed MPC with particle swarm optimization (PSO) tuned PID controller.

1.5 Thesis Structure and Organization

Chapter 2 discusses membrane bioreactor and the existing filtration systems. This chapter also reviews on the operation of the SMBR and the current cleaning mechanism of the filtration process in dealing with fouling phenomena for SMBR system. The modeling technique also discussed in this chapter, focusing on the application of artificial intelligent and soft computing techniques in the modeling of the filtration process. The application of controllers in SMBR also discussed and elaborated.

Chapter 3 explains the methodology of the modeling for the SMBR filtration process. The plant development and the experimental setup of the SMBR presented at the beginning of this chapter. Then, systematic modeling techniques including the model training and evaluation methods presented. In this chapter, the proposed algorithms for training ANN model introduced. This chapter also includes the verification on the proposed algorithm using ten benchmark functions and another data set, which is the heating process data set.

Chapter 4 introduces on the controller development. This includes the PID controller design with PSO tuning method. This chapter also discusses the methodology neural network model predictive controller design with different real-time optimization strategies.

Chapter 5 presents and discuss on the modeling result of the SMBR filtration. This chapter also reveals on the performance of the proposed algorithms on training the ANN model and minimizing benchmark functions. Finally, this chapter presents the performance of NNMPC in controlling the filtration process and the comparison of its performances with PID controller.

Chapter 6 presents the conclusion for the thesis. The potential future works recommended at the end of this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents a review on the modelling and control of submerged membrane bioreactor (SMBR) filtration system. In general, detail review is given on the modelling, optimization and control of the SMBR. As the work focusing on fouling control, more detail review on fouling in SMBR filtration and fouling control operation such as aeration airflow, backwash and relaxation is given.

Basically, this review is divided into several main parts. First, review on MBR filtration modelling and control is presented. Then, due to the non-linearity of the filtration process and almost impossible to represent it using standard mathematical equation, the artificial neural network (ANN) is investigate and reviewed. For better prediction and control of SMBR filtration model, ANN with soft computing approach such as GSA, PSO and hybrid PSOGSA is also reviewed.

Furthermore, the model predictive control (MPC) is presented. As the MBR filtration is a nonlinear process, the neural network model predictive control (NNMPC) is also reviewed.

2.2 Membrane Bioreactor

Membrane technology has become significantly important in filtration systems and has become a requirement in wastewater treatment technology. As reported by [15], the application of MBR technology in many parts of the world has grown significantly over last few years. This showing the MBR is a superior technology in wastewater treatment either for domestic or industrial. With more stringent effluent requirements and environmental concerns, as well as water protection awareness, membrane technology is one of the promising techniques that can resolve the quality issue in wastewater treatment process.

Membrane bioreactor system for wastewater treatment is the combination of membrane filtration with bioreactors that treat wastewater. The bioreactor in MBR wastewater treatment process is a place where the influent biologically treated. The configuration of membrane bioreactors divided to two well-known architectures of MBR systems which are side-stream membrane bioreactor and submerged membrane bioreactor (SMBR).

2.2.1 Side stream membrane bioreactor

Side stream MBR system or also known as cross-flow membrane MBR the filtration system located on the outside of the bioreactor tank. This filtration system is also known as the crossflow filtration system. In this configuration, the treated influent will pumped to the filtration module under the allowable pressure requirement by the manufacturer. The filtrate effluent is called permeate flux. The side-stream membrane filtration system also is suitable for other separation applications such as food processing, desalination and drinking water process. Figure 2.1 shows the configuration of the side-stream MBR filtration process.

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APPENDIX A

LIST OF PUBLICATIONS

A.1 Journal Papers

1. **Zakariah Yusuf,** Norhaliza Abdul Wahab, Shafis huhaza Sahlan, Permeate Flux Measurement and Prediction of Submerged Membrane Bioreactor Filtration Process Using Intelligent Techniques, *Journal Teknologi*, 2015.(SCOPUS)
2. **Zakariah Yusuf**, Norhaliza Abdul Wahab, Shafis huhaza Sahlan, Fouling control strategy for submerged membrane bioreactor filtration processes using aeration airflow, backwash, and relaxation: a review, *Desalination and Water Treatment*, 57:38, pp17683-17695, 2016. (SCOPUS/ISI-JCR IF 1.631)
3. **Zakariah Yusuf**, Norhaliza Abdul Wahab, Shafis huhaza Sahlan, Fouling effect on controller tuning in membrane bioreactor, *Journal Teknologi*, 2016. (SCOPUS)
4. **Zakariah Yusuf**, Norhaliza Abdul Wahab, Shafishuhaza Sahlan,Dynamic modelling and control of membrane filtration process, *Int. J. of Nanotechnology*, Vol.13, No.10/11/12, pp.748 – 763, 2016. (SCOPUS/ISI-JCR IF 0.5)
5. **Zakariah Yusuf**, Norhaliza Abdul Wahab,Abdallahh Abusam, Neural Network-based Model Predictive Control with CPSOGSA for SMBR Filtration, *International Journal of Electrical and Computer Engineering (*IJECE), Vol 7, 2017. (SCOPUS).

A.2 Conference Papers

1. **Zakariah Yusuf**, Norhaliza Abdul Wahab & S. Sahlan, Modeling of Submerged Membrane Bioreactor Filtration Process Using NARX-ANFIS Model, *IEEE conference 10th ASIAN CONTROL CONFERENCE 2015 (ASCC 2015)*, 31st May– 3rd June 2015 , Sutera Harbour Resort, Sabah, MALAYSIA
2. **Zakariah Yusuf**, Norhaliza Abdul Wahab, Mohd Hakim Abd Halim, Aznah Nor Anuar, Zaini Ujang, Mustafa Bob (2015), Modeling of SBR Aerobic Granular Sludge Using Neural Network ith GSA and IW-PSO, *IEEE conference 10th ASIAN CONTROL CONFERENCE 2015 (ASCC 2015)*, 31st May– 3rd June 2015 , Sutera Harbour Resort, Sabah, MALAYSIA
3. **Zakariah Yusuf**, Norhaliza Abdul Wahab & S. Sahlan (2015), Dynamic Model Development for Submerged Membrane Filtration Process with Control Application, *1st ICRIL-International Conference on Innovation in Science and Technology*, 2015
4. **Zakariah Yusuf**, Norhaliza Abdul Wahab & S. Sahlan, (2015) Modeling of Activated Sludge Process Using Various Nonlinear Techniques: A Comparison Study, *1st ICRIL-International Conference on Innovation in Science and Technology*, 2015.
5. **Zakariah Yusuf**, Norhaliza Abdul Wahab & S. Sahlan, (2017) Cooperative PSOGSA Using Multiple Groups Approach for Functions Optimization, *ASIASIM* 2017. (**Accepted**)