UNIVERSITI PUTRA MALAYSIA

MODELLING OF BIOGAS PRODUCTION PROCESS WITH EVOLUTIONARY ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM

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By

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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July 2017

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In recent years, several researchers have actively pursued the application of machine learning to biogas production processes. The application of artificial neural network (ANN) to generate the production model is used to improve the modelling accuracy. The model output optimisation by genetic algorithm (GA) produces higher biogas production compared to the optimisation using statistical methods.

This study utilised the evolutionary artificial neural network (EANN) modelling to improve the model accuracy. The EANN modelling was used to represent the biogas production process. One of the issues of ANN implementation is to correctly select the output activation function in achieving higher output. The EANN used a modified activation function to meet the optimisation requirement.

To evaluate the EANN model, 19 samples of experimental data from Zainol on the regression modelling of biogas production from banana stem waste were selected. Thirteen samples were used for training (70%) and six samples were used for testing (30%). The second dataset from Mahanty which consisted of 36 samples on the modelling and optimisation of biogas production from industrial sludge were divided into 25 training samples and 11 testing samples. Meanwhile, 34 samples from Tedesco on the optimisation of mechanical pretreatment of *Laminariaceae* spp. biomass for the production of biogas were divided into 24 training samples and 10 testing samples. The last dataset from the domain expert containing 143 samples were divided into 100 training samples and 43 testing samples.

The model performance was evaluated using root mean square error (RMSE) and coefficient of determination (R^2) and the maximum output from the

optimisation was compared to the mathematical modelling. The experiment was conducted with 50 trial runs on each dataset and EANN method produced better modelling results compared to the mathematical modelling. The model output from the optimisation using GA also produced better results than the mathematical model and able to limit the maximum output of the back-propagation and Levenberg-Marquardt ANN models which used linear function output.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PERMODELAN PROSES PENGHASILAN BIOGAS MENGGUNAKAN RANGKAIAN NEURAL BUATAN TEREVOLUSI DAN ALGORITMA GENETIK

Oleh

ABDUL SAHLI BIN FAKHARUDIN

Julai 2017

Pengerusi: Prof. Madya Md Nasir bin Sulaiman, PhD
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Sejak kebelakangan ini, terdapat penyelidik yang aktif menggunakan aplikasi pembelajaran mesin di dalam proses penghasilan biogas. Penggunaan rangkaian neural buatan untuk memodelkan proses penghasilan tersebut telah meningkatkan kejituan model. Pengoptimuman model output oleh algoritma genetik menghasilkan biogas yang lebih tinggi berbanding pengoptimuman menggunakan kaedah statistik.

Kajian ini telah menggunakan rangkaian neural buatan terevolusi untuk meningkatkan kejituan model. Rangkaian neural buatan terevolusi digunakan untuk mewakilkan proses penghasilan biogas. Salah satu isu di dalam penggunaan rangkaian neural buatan ialah pemilihan fungsi pengaktifan yang betul dalam mencapai output yang lebih tinggi. Rangkaian neural buatan terevolusi telah menggunakan fungsi pengaktifan yang telah diubahsuai untuk memenuhi keperluan proses pengoptimuman.

Untuk menilai model rangkaian neural buatan terevolusi, 19 sampel data eksperiman Zainol yang menggunakan permodelan regresi untuk penghasilan biogas dari sisa batang pisang telah dipilih. Tiga belas sampel digunakan untuk set latihan (70%) dan enam sampel digunakan untuk set pengujian (30%). Set daata yang kedua adalah dari Mahanty yang mengandungi 36 sampel permodelan dan pengoptimuman proses penghasilan biogas dari enap cemar industri, telah dipecahkan kepada 25 set latihan dan 11 sampel pengujian. Manakala, 34 sampel dari Tedesco bagi pengoptimuman proses pra-rawatan mekanikal biomas *Laminariaceae* spp. untuk peghasilan biogas telah dibahagikan kepada 24 sampel latihan dan 10 samapel pengujian. Data terakhir daripada pakar domain yang mengandungi 143 sampel dan telah dibahagikan kepada 100 sampel latihan dan 43 sampel pengujian.

Prestasi model telah dinilai menggunakan punca kuasa min ralat dan pekali penentuan dan maksimum output dari proses pengoptimuman telah dibandingkan dengan permodelan matematik. Ujikaji telah dijalankan dengan 50 larian bagi setiap set data dan kaeda rangkaian neural buatan terevolusi menghasilkan keputusan model lebih baik dari permodelan matematik. Model output melalui pengoptimuman algoritma genetik juga menghasilkan keputusan lebih baik daripada model matematik dan dapat menghadkan output maksimum dari rangkaian neural buatan perambatan balik dan Levenberg-Marquardt yang menggunakan fungsi linear pada output.

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I certify that a Thesis Examination Committee has met on 20 July 2017 to conduct the final examination of Abdul Sahli Fakharudin on his thesis entitled Modelling of Biogas Production Process with Evolutionary Artificial Neural Network and Genetic Algorithm in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BP	Back-propagation
COD	Chemical Oxygen Demand
EANN	Evolutionary Artificial Neural Network
GA	Genetic Algorithm
HRT	Hydraulic Retention Time
LM	Levenberg−Marquardt
MSE	Mean Square Error
NEAT	NeuroEvolution of Augmenting Topologies
OLR	Organic Loading Rate
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
RSM	Response Surface Methodology

CHAPTER 1

INTRODUCTION

This chapter will provide the background of previous studies, problem statements, objectives and scope of the study including the predicted output. It also contained research benefits and overall organisations of the thesis to give a general perspective of the research flow.

1.1 Background

The consumption of renewable energy from 2000 to 2011 has increased by 30% and the highest absolute increase among the renewable energy consumption was the bioenergy source (WBA, 2014). The bioenergy categories into the solid biomass, liquid biofuels, wastes and biogas. Interest in converting biomass resources to an alternative fuel such as biogas, have received more attention in recent times (Yang et al., 2013). A feasibility study on biogas production and utilisation as a source of renewable energy in Malaysia by Hosseini and Wahid (2013) discussed the used of palm oil industry by-product as the sources to extract biogas. A review by Ahmed et al. (2015) presented the biogas production and performance evaluation of the treatment process from palm oil mill effluent.

This biogas yield can be improved with better process design, which include the modelling, simulation and optimisation process as an integrated part of modern design practice (Betiku and Ajala, 2014). Work by Sendjaja et al. (2015) mentioned about two main types of modelling approach in anaerobic digestion, including biogas production, which are the mathematical based model derived from mathematical equations and data or statistical approach using multivariate regression and machine learning approach.

Modelling of biogas generation using mathematical and statistical approach was a proven knowledge used by many researchers (Zainol et al., 2009; Mahanty et al., 2014; Tedesco et al., 2014). They used a regression model to represent their process and the model output was being optimised using statistical method to obtain the maximum biogas output. The predicted maximum biogas output from the generated model was presented and its successfully improved the biogas output from the actual production.

The improvement of the biogas production using modern computer science field also has advantages than the mathematical modelling. Such area that is being explored (Behera et al., 2015; Dhussa et al., 2014; Yetilmezsoy et al., 2012) was a specific intelligent computing area, which used artificial neural networks (ANN) to model their process. These researchers had reported the application of ANN had succeeded to model their biogas production process. Most of the ANN training (Yetilmezsoy et al., 2012; Abu Qdais et al., 2010) was set from a small number of hidden neurons to the maximum number according to each specification.

1.2 Problem Statements

This study addressed the problem of the model output optimisation done by Akbaş et al. (2015) which unable to generate higher output (Abu Qdais et al., 2010; Gueguim Kana et al., 2012) than the actual process. He used ANN modelling with hyperbolic tangent as the activation function and the maximisation of biogas output was limited to highest function range. The optimal biogas output from the model could not achieve the actual biogas output let alone more than it.

Gueguim Kana et al. (2012) used ANN modelling with linear activation function and the optimisation process produced higher maximum output than the actual process because the linear function was not limited to a certain maximum range. The implementation of linear activation on output layer made it as a threshold layer even the hidden layer used sigmoid activation function. If the linear function output being optimised by an efficient optimiser, then the maximum output value could produce a very high, unrealistic output, because the unlimited range of the linear activation function.

It is important to develop a predictive model for engineering process that can maximise the production. A proper implementation of specialised ANN with a modified activation function should be able to regulate the network output from producing an unlimited output and should be able to produce maximum output more than one to ensure the model output is better than the actual output.

1.3 Objectives

The main objective of this research is to model the biogas process with evolutionary artificial neural network (EANN) for optimum production. The specific objectives of this research are as follows:

1. To propose an implementation of evolutionary artificial neural network modelling to improve the mathematical modelling accuracy of biogas process.
2. To propose a modified activation function in evolutionary artificial neural network modelling to find the best biogas representation and to fulfil the output optimisation requirements.
3. To propose an appropriate parameter for genetic algorithm to optimise the selected biogas process representation.

1.4 Scope of Study

The study used a dataset from Zainol et al. (2009) in order to model the biogas process where she used mathematical modelling and optimisation of biogas production from banana stem waste. Three additional datasets also being used to determine the model accuracy improvement and the output optimisation comparison. These four datasets will be normalised and divided into training and testing set.

The results from the modelling of biogas process representation will be evaluated using root mean square errors (RMSE) and correlation determination (R^2) for performance evaluation. The accuracy measurements were based on traditional ANN evaluation with an additional engineering process modelling validation.

The best model will be selected and it will be used to find the optimal biogas output using the genetic algorithm (GA). The predicted optimised output will be collected from the model output and will be compared with the mathematical optimisation.

1.5 Research Benefits

There are two main benefits of this research:

1. The EANN modelling for biogas production representation; it will be proposed as an alternative to ANN which reduce the guesswork and complexity.
2. The modified activation function; it will present the important of specific ANN design and architecture in solving a problem even though the ANN generalisation mostly works.

1.6 Organisation of the Thesis

The thesis consists of six chapters. Chapter 1 discussed the introduction to biogas production modelling and optimisation. The purpose of this chapter was to explain the problem statements, objectives of the study, the scopes of the study and the benefits. It concluded by the organisation of the thesis.

In Chapter 2 it discussed the literature review of the research. This chapter contains the information on the biogas production and research related to the topic. Followed by the previous study of modelling of biogas production from waste using a mathematical approach. The next part discussed about the ANN and the used of ANN for modelling and followed by previous study that used ANN for modelling biogas production. The next topic discussed about issues in ANN modelling and suggested solutions. The final part of the chapter discussed about GA and the previous study which utilising GA optimisation.

The next Chapter 3 discussed about the research methodology to perform the modelling and optimisation process. It started with the research framework followed by the biogas production data processing. The brief information of biogas modelling and optimisation was presented next. The experimental setup was discussed later followed by the evaluation on both modelling and optimisation results.

In chapter 4, the details of the modelling and optimisation of biogas production were presented. The EANN modelling was discussed first and followed by the benchmark modelling. The optimisation of the model using GA algorithms was discussed last on this chapter.

Chapter 5 presented the results of the modelling using EANN and the benchmark modelling. It followed by the details on the result of GA optimisation from the models generated by EANN and ANN.

Finally, chapter 6 concluded the findings. The purpose of this chapter is to make the conclusion of the research and the future research that can be continued from this research.

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