

VOL. 72, 2019



DOI: 10.3303/CET1972053

#### Guest Editors: Jeng Shiun Lim, Azizul Azri Mustaffa, Nur Nabila AbdulHamid, Jiří Jaromír Klemeš Copyright © 2019, AIDIC Servizi S.r.I. ISBN 978-88-95608-69-3; ISSN 2283-9216

# Predictive Modelling for Biogas Generation from Palm Oil Mill Effluent (POME)

## Nur Hazirah Che Ithnin, Haslenda Hashim\*

School of Chemical and Energy Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia haslenda@cheme.utm.my

Palm oil mill effluent from palm oil production has seen to be a valuable waste resource for biogas recovery. Nonetheless, there is lack of study on specifically identifying significant biogas-production parameters and its correlations that will further enhance biogas recovery. In addition, there is also absence of a study to further exploit these relations in predicting parametric inputs and outputs to be applied in an interwoven relation known as the wastewater-energy nexus. Thus, this study aims to establish a predictive modelling approach through regression analysis on study parameters to predict biogas yield. In addition, predictive assessment on economic and environmental implications from the predicted biogas production is also carried out. The results demonstrated a relatively high correlation between various pairs of biogas-producing parameters with R square values higher than 60 %. An illustrative scenario analysis is presented in order to demonstrate the applicability of this predictive modelling approach. A Sankey diagram is also presented to illustrate the application of the model and the implication of wastewater-energy nexus. This study is intended to be of significant importance to predict parametric control of POME on biogas generation which in hand will deliver economic advantages to the palm oil mill industry as well as environmental benefits to the natural ecosystem.

## 1. Introduction

Malaysia is one of the largest producers in the palm oil industry, accounting up to 39 % of the world palm oil production, placing second after Indonesia. In the year 2017, crude palm oil (CPO) production increased by was a massive 19.92 Mt (Malaysia Palm Oil Board Department of Statistics, 2017). Nonetheless, despite the promising market of palm oil leading to increased production, it has consequently been seen that relatively large amounts of biomass waste are produced where POME contributes to the largest portion of waste production with 53 Mm<sup>3</sup> of POME being produced in Malaysia, annually. With massive volumes of waste generated available in treating POME, various methods of treatment are carried out in order to reduce the negative effects of palm oil mill effluent wastewater accumulation (Zainal et al., 2017). One of the most approachable methods is through the wastewater treatment using an anaerobic bioreactor. Consequently, this digestion not only reduces the amount of unwanted compounds in the wastewater but also allows tapping of biogas, specifically methane gas, CH<sub>4</sub>, a great form of renewable energy. Hence, through this general observation, a specific study is carried out in order to identify the significant parameters that will significantly affect biogas yield. Ultimately, the prediction in regards to the amount of biogas and energy that can be produced is able to be carried out. Scenario analysis of economic implications of the predictive biogas and energy generation for the wastewaterenergy nexus and environmental implications with emphasis on possible mitigation of greenhouse gas (GHG) emissions which are avoidance of CO<sub>2</sub> emissions towards the environment will also be carried out. On overall, this could provide a better predictive insight in regards to parametric control of POME towards energy production and consumption as well as economic and environmental impacts, nationally and globally as a whole.

## 2. Literature review

Past studies have also shown the variations in predictive modelling approaches that were adopted to predict biogas generation. Amongst them is through theoretical biochemical equation where according to Nielfa et al. (2014), the methane potential could be calculated through the available amount of material and chemical oxygen

Paper Received: 26 September 2018; Revised: 11 October 2018; Accepted: 28 October 2018

Please cite this article as: Che Ithnin N.H., Hashim H., 2019, Predictive modelling for biogas generation from palm oil mill effluent (pome), Chemical Engineering Transactions, 72, 313-318 DOI:10.3303/CET1972053

#### 314

demand (COD) concentration which employs a theoretical biochemical approach. Additionally, statistical analysis which is rather well-established has also been utilized in the prediction of biogas generation from substrate loadings of municipal solid waste (MSW) in the study of Ojolo et al. (2008). Modelling through mathematical equations based on kinetic behaviour has also been practiced. Adamu and Aluyor (2013) in their study applied empirical models which are the Gompertz and Modified Logistics models to predict biogas generation from cattle dung. In the prediction of biogas generation, fuzzy logic was also seen as a viable tool. According to a study by Turkdogan-Aydınol and Yetilmezsoy (2010), the multiple input and multiple output (MIMO) fuzzy model was employed in predicting biogas generation from molasses wastewater parameters. Moreover, there is also the neural network which has been applied in order to predict biogas generation. In a study by Thomas et al. (2017), they adopted extremal neural network modelling to predict biogas generation from the organic fraction of municipal solid wastewater and wastewater sludge. The outcomes showed that the developed model was able to be used to further predict power production and aid in identifying the most suitable conditions or parameters for the model. A similar approach has also been adopted in the study of Leite et al. (2018) on a prediction of biogas production on a swine farm. In their study, it was concluded that chemical parameters associated with the information (inputs and outputs) from the swine production were important to design and improve biodigesters. A hybrid approach of fuzzy model and artificial neural network known as Adaptive Neuro-Fuzzy Inference System (ANFIS) applied in the study of Santos et al. (2017) is another predictive method used in the prediction of parameter inputs and outputs. The study was able to produce a dynamic predictive model of a non-linear fermentation process from the hybrid approach. In the case of palm oil mill effluent, in terms of the observations on parameter influence towards biogas generation, past studies have shown an extent of influence from physicochemical properties such as pH, COD removal, free fatty acid percentage in POME (Xu et al., 2014), and temperature (Sri Rahayu et al., 2015).

#### 3. Methodology

#### 3.1 Data collection and chemical analysis

Data were collected from two palm oil mills for a duration of 28 d, namely plant A and plant B which installed the biogas capture for energy generation from POME. These factories are located within the state of Johor and both plants have an energy generation capacity of 2 MW. Chemical analysis was then performed though manual laboratory tests on the POME samples which were collected on a daily and collective weekly basis in order to gauge the quality of the biological wastewater through identification of physicochemical parameters. The identified parameters include pH, temperature of anaerobic digestion, COD levels, COD removal percentage as well free fatty acid (FFA). Other forms of data such as fresh fruit bunch (FFB) feed input and POME generation amount were also collected in order to obtain important information to identify specific factors and its correlation towards biogas production.

#### 3.2 Regression analysis

The application of statistical analysis which involves an approach through data collection leading towards uncovering trends or certain patterns is a well-established method in studying parametric control. Thus, this method was used in the study. The specific type of statistical tool which was adopted was a regression analysis. Regression allowed the comprehension of the relation between independent variables with dependent variables and allows further exploration on the forms of these relations. In this study, the relationship of the study parameters from plant A towards biogas production were analyzed using multiple linear regression through determination of correlation coefficients, r and R-squared values. The correlation coefficient was obtained using a mathematical formula based on the Karl Pearson's Coefficient of Correlation.

#### 3.3 Relation of predictive modelling towards wastewater-energy nexus

With the regression relations in hand, the predictive modelling enabled varying input conditions to be tested out for predicting outcomes of the biogas production or predicting other additional outputs such as the amount of POME that would be required to generate a pre-determined volume of biogas. Conclusively, the information was used in order to predict the amount of energy that could be obtained through the wastewater-energy nexus. The visualization of the predictive outcomes of the nexus based on a pre-determined set of conditions was then demonstrated with the aid of a Sankey Diagram. The Sankey diagram involved the material and energy balance within the biogas capture system from POME of the palm oil mill plant.

#### 3.4 Assumption

A theoretical assumption was made in the conversion from the volume of biogas to energy generated whereby 1 m3 generated 2 kWh of energy. This assumption is used based on literature (Quebec Association for the Production of Renewable Energy (AQPER), 2018).

### 4. Results and discussion

#### 4.1 POME wastewater quality analysis

Based on a laboratory chemical analysis of the POME wastewater samples from plant A and plant B, results of the value ranges of operating parameters and physicochemical parameters were reported as seen in Table 1.

Table 1: Operational and psychochemical parameter value ranges of POME wastewater samples from plant A and plant B

No	Parameter	Plant A	Plant B
1	FFB daily feed input (MT)	854 – 1,773	1,584 – 1,684
2	POME generation amount (m <sup>3</sup> )	556 – 1,170	363 - 541
3	FFA of POME (%)	3.00 - 4.00	2.62 – 4.16
4	Temperature during anaerobic digestion (°C)	36 – 37	41 - 44
5	pH for anaerobic digestion	7.30 - 7.40	7.10 – 7.87
6	COD removal (%)	91.49 – 94.32	69.00 - 84.00
7	Initial POME COD (mg/l)	69,700 - 91,300	51,000 - 92,000
8	Final POME COD (mg/l)	4,450 - 6,450	12,000 - 37,000

#### 4.2 Linear and multilinear regression correlation of physicochemical parameters

Linear and multilinear regression relations were produced in this study to view the single and simultaneous correlations of a set of variables towards a dependent parameter. Based on the scale of the Pearson Coefficient Correlation in Figure 1, it is evident that the biogas production is relatively strongly correlated to the pairs of parameters demonstrated in Table 2 and Table 3 where each table shows linear and multilinear regression relations together with their strength of correlation coefficient.

	Nega	ative Co	orrela	ation	No Corre	elation	Pos	sitive Correl	ation
	Strong	Moder	rate	Weak			Weak	Moderate	Strong
-	1 -0	.8	-0.	5 -0	0.2 0	0.	2 0.	5 0.	.8 1

Figure 1: Pearson Correlation Coefficient Strength Scale (Heiman, 2011)

Table 2: Linear	rearession	relations	based c	on different	pairs of	<sup>;</sup> parameters

Pairs of Parameter	Linear regression equation	Correlation coefficient, r	R square (%)
Biogas-POME generation	y =36.658 x + 1,139.7	0.9939	98.78
Biogas-pH	y= -372,221 x + 3E+06	0.9210	84.82
Biogas-Temperature	y = - 937,779.83 + 24,238.76 x	0.9519	90.61
Biogas-COD removal	y = - 67,664.02 + 1,048.42 x	0.9566	91.50
COD removal-FFA	y = 105.10 - 3.26 x	-0.9007	81.13

Table of Malanteal regreeoler relatione bacea en aneren en combinatione er parameter	Table 3: Multili	inear regression	relations base	d on different o	combinations of	<sup>i</sup> parameters
--	------------------	------------------	----------------	------------------	-----------------	-------------------------

Sets of Parameter	Multilinear regression equation	Correlation coefficient, r	R square (%)
Biogas = y	y = -3,426.51 x1 + 843.58 x2	0.9341	87.25
FFA percentage = x1	- 3,5648.79		
COD removal = x2			
Biogas = y	y = -98,523.85 x1 - 1,510,022.38 x2	0.7869	61.92
FFA percentage = x1	+ 12,314,571.79		
pH = x2			
Biogas = y	y = -667,151.34 x1 + 25,297.48 x2	0.9989	99.78
pH = x1	+ 4,237,514.06		
Temperature = x2			
Biogas = y	y = -1,410.94 x1 + 17,593.11 x2	0.9804	96.12
COD removal = x1	- 536,922.25		
Temperature = x2			
Biogas = y	y = -4,026.00 x1 + 641,696.33 x2	0.9032	81.57
COD removal = x1	- 4,585,692.56		
pH = x2			

In the instance of the linear regression relation between temperature and biogas production as seen in Table 2, the correlation coefficient value of 0.9519 demonstrates a strong, positive affect of temperature towards biogas production. In other words, the higher the mesophilic temperature during POME digestion, the higher the generation of biogas. In another instance referring to Table 3 of multilinear regressions, taking sets of parameters of biogas generation, pH and temperature, the 0.9989 value shows that all three parameters are highly correlated towards each other. This shows that changes in both pH and temperature would significantly affect biogas production. Figure 2 demonstrates an example amongst the varying possible multilinear regressions in this study whereby in this example, the influence of FFA in POME and COD percentage removal towards biogas production was studied. The multilinear regression relation formed is  $y = -3,426.51 \times 1 + 843.56 \times 2 - 35,648.79$  where x1 is FFA percentage in POME and x2 is percentage of COD removal while y predicts the biogas generation. The correlation coefficient of this relation has a value of 0.9341 which shows that both the independent variables highly affect the dependent variable which is the amount of biogas produced. Additionally, applying the multilinear regression equation from Table 3, it can be inferred from Figure 2 that the optimal condition for biogas production in this specific example is met at a FFA percentage of 3.8 % and at a COD percentage removal of approximately 92.7 %. This produced biogas production of 29,500 m<sup>3</sup>.







#### 4.3 Production of wastewater-energy nexus with parametric control - model fitting

Through the predictive modelling approach of physicochemical parameters in POME, it can also be said that the input and output parameters can be manipulated and controlled by the user based on the regression relations to suit the needs of the palm oil mill. A set of pre-determined conditions of the POME wastewater parameters enables the biogas production to be predicted. This consequently also leads to the prediction of the amount of energy that can be produced. The relation of the POME wastewater and energy production demonstrates a nexus where the wastewater will produce energy and this energy is returned back to the mill to reproduce wastewater.

As the amount of energy can be predicted through the input or parametric control, the distribution of energy in the form of electricity to be sold to the National Grid or used by the mill could be also predicted. In order to test and fit the model in relation to wastewater-energy nexus, pre-determined or illustrative conditions were applied in the conduct of this scenario analysis. The predetermined input in this illustration is an FFA percentage in POME of 3 % while the predicted outcomes are the POME generation, COD removal and biogas generation on a per daily basis. The equations that have been used in the illustrative scenario are as seen in Eq(1), Eq(2) and Eq(3) which have been specifically chosen from Table 3.

y = 105.10 - 3.26 x	(1)
y = -3,426.51 x1 + 843.58 x2 - 3,5648.79	(2)

y = 36.67 x + 1,139.7(3)

316

Table 4 below further demonstrates on the outcomes of the illustrative scenario based on the pre-determined condition of 3 % FFA in POME.

Table 4: Illustrative scenario and	lysis case based on	input of FFA
------------------------------------	---------------------	--------------

Subject	Value		
FFA in POME (%)	3		
Predicted COD removal (%)	95.33		
Predicted POME Generation per day (m <sup>3</sup> /d)	909.76		
Predicted Biogas Generation per day (m <sup>3</sup> /d)	34,489.70		
Predicted Energy Generation per day (kWh/d) 68,979.40			

Considering all the power export to the mill to produce POME, the amount of POME regenerated is 1205 m<sup>3</sup>/d. This is based on 17 kWh electricity consumed for every 1 m<sup>3</sup> of POME being produced according to Yusniati et al. (2018). A Sankey diagram as seen in Figure 3 is displayed as a visualization tool of the modelled and predicted scenario which was based on the initial input of a POME wastewater content with 3 % FFA.



Figure 3: Sankey Diagram based on illustrative conditions and predicted outcomes of biogas and energy generation from POME wastewater.

#### 4.4 Economic and environmental predictive assessment

Based on the predicted biogas and energy generation obtained through the regression analysis, an additional economic predictive assessment was carried out. Table 5 demonstrates these results based on the illustrative case in Table 4, it is estimated based on the case of plant A that the average power exported to the TNB grid to be sold is 67 % of the total daily energy generation which will firstly deduct an approximate 10 % as heat loss. In the instance of the illustrative case in Table 4, the predicted average power to be exported to the grid is 41,594.58 kWh. The balance after selling electricity to the National Grid will only then be exported for internal use to the palm oil milling processes with an amount of 20,486.88 kWh. This is because sales to the National Grid will produce a higher revenue in comparison to the savings that will be obtained from internal use. In other words, the selling price of electricity is higher than the electricity cost to be bought for the facility use.

Table 5: Predicted monetary revenue and cost savings from illustrative case for a per day basis

	Amount of Energy (kWh)	Monetary Value (MYR)
Predicted energy export to TNB	41,594.58	19,549.45
Predicted energy export to mill	20,486.88	6,904.08

With the selling price of electricity at 0.47 MYR/kWh, predicted revenue from electricity sold to TNB is 19,549.45 MYR. On the other hand, with an electricity cost of 0.3370 MYR/kWh based on the TNB electricity tariff schedule, the predicted cost savings from self-electricity production for the palm oil mill is as much as MYR 6,904.08 (Tenaga Nasional Berhad, 2014). Thus, the total revenue predicted based on the illustrative case for a one-day

case is 26,453.53 MYR. The results demonstrate that revenue and cost savings can be easily predicted based on the regression model produced. This will certainly be helpful in cost-related decision-making in palm oil mill companies and can also be used as a financial forecast tool. Additionally, prediction on environmental conditions were also attained. Once again, from the illustrative case in Table 4, if biogas was instead not captured and was then released into the environment, based on the standard formulation by the GHG Protocol for CO<sub>2eq</sub> emissions, the predicted emissions amounted to 579,426.96 t of CO<sub>2eq</sub>/d.

## 5. Conclusion

Predictive modelling to estimate the biogas yield has been successfully developed in this study. It was found that the significant parameters towards biogas production from POME are pH, temperature, COD removal percentage, POME generation and FFA percentage which strongly agrees with past studies. The linear and multilinear regressions constructed in this study demostrate the correlation strengths of various parameters. The predictive assessment on economic and environmental implications of biogas generation from POME is an additional forecast tool which is also beneficial. The Sankey diagram of the wastewater-energy nexus visualizes and ties all the findings as a whole where it is a good representation in understanding the network system.

## Acknowledgments

The author would like to acknowledge the financial support in the form of research grant by UTM with grant no.Q.J130000.2546.20H10.

#### References

Adamu A.A., Aluyor, E. O., 2013, Empirical model for predicting rate of biogas production. Global Journal of Engineering Research, 12, 63-68.

- Heiman, G.W., 2011, Basic Statistics for the Behavioral Sciences, 6<sup>th</sup> Edition, Wadsworth Cengage Learning, California, United States, 142-145.
- Leite S., Leite B., Figueiredo M., Dell'Isola A.T., Dangelo J.V., 2018, Biogas production on a small swine farm: study of prediction using different models, Chemical Engineering Transactions, 65, 85-90.
- Malaysia Palm Oil Board Department of Statistics, 2017, Report: Overview of the Malaysian Oil Palm Industry 2017 <br/>
  composition of the Malaysian Oil Palm Industry 2017 <br/>
- Nielfa A., Cano R., Fdz-Polanco M., 2014, Theoretical methane production generated by the co-digestion of organic fraction municipal solid waste and biological sludge, Biotechnology Reports, 5, 14-21.
- Ojolo S., Bamgboye A., Ogunsina B., Oke S., 2008, Analytical Approach for Predicting Biogas Generation in a Municipal Solid Waste Anaerobic Digester, Iranian Journal of Environmental Health, Science and Engineering, 5, 179-186.
- Quebec Association for the Production of Renewable Energy (AQPER), 2018, BIOGAS: How much energy is there in biogas? <a provide a comparison of the energy-is-there-in-biogas > accessed 19.06.2018.
- Santos B., Ponezi A., Fileti A.M.F., 2017, Development of artificial intelligence models to monitor biosurfactant concentration in real-time using waste as substrate in bioreactor through fermentation by bacillus subtilis, Chemical Engineering Transactions, 57, 1009-1014.
- Sri Rahayu A., Karsiwulan D., Yuwono H., Trisnawati I., Mulyasari S., Rahardjo S., Paramita V., 2015, Handbook: POME-to-Biogas Project Development in Indonesia <www.winrock.org/wpcontent/uploads/2016/05/CIRCLE-Handbook-2nd-Edition-EN-25-Aug-2015-MASTER-rev02-final-new02edited.pdf> accessed 13.04.2018.
- Tenaga Nasional Berhad, 2014, Electricity Tariff Schedule
- <www.tnb.com.my/assets/files/Tariff\_Rate\_Final\_01.Jan.2014.pdf> accessed 19.06.2018.
- Thomas P., Debnath T., Soren N., 2017, Forecasting and analysis of biogas-based power production using extremal neural network, Energy Sources, Part B: Economics, Planning, Policy, 12(8), 730-739.
- Turkdogan-Aydınol F. I., Yetilmezsoy K., 2010, A fuzzy-logic-based model to predict biogas and methane production rates in a pilot-scale mesophilic UASB reactor treating molasses wastewater, Journal of Hazardous Materials, 182(1-3), 460-471.
- Xu Z., Zhao M., Miao H., Huang Z., Gao S., Ruan W., 2014, In situ volatile fatty acids influence biogas generation from kitchen wastes by anaerobic digestion, Bioresource Technology, 163, 186-192.
- Yusniati Y., Parinduri L., Sulaiman O.K., 2018, Biomass analysis at palm oil factory as an electric power plant, Journal of Physics: Conference Series, 1007, 1-6.
- Zainal N.H., Jalani N.F., Mamat, R., Astimar A.A., 2017, A review on the development of palm oil mill effluent (POME) final discharge polishing treatments, Journal of Oil Palm Research, 29, 528-540.

#### 318