DATA-DRIVEN MODELLING AND OPTIMIZATION OF PALM OIL REFINING PROCESS

NURUL SULAIHA BINTI SULAIMAN

UNIVERSITI TEKNOLOGI MALAYSIA

DATA-DRIVEN MODELLING AND OPTIMIZATION OF PALM OIL REFINING PROCESS

NURUL SULAIHA BINTI SULAIMAN

A thesis submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy (*Chemical Engineering*)

School of Chemical and Energy Engineering Faculty of Engineering Universiti Teknologi Malaysia

SEPTEMBER 2021

ACKNOWLEDGEMENT

Greatest thanks to the Almighty ALLAH S.W.T for His divine blessing and assists throughout the research. I would like to appreciate Professor Dr. Khairiyah Muhd Yusof for her support, understanding, and motivation during my PhD study. Her guidance helped me all the time of the research and writing of this thesis.

Next, I would like to express my sincere gratitude to Encik Asngari Saion and Sime Darby Kempas Sdn. Bhd. for the useful information and data provided for this research. On the other hand, I would like to express my special appreciation to my mother, Puan Hamidah binti Rasiman, for her infinite love, support, and motivation. Without her support, I can't come out with this thesis.

My sincere thankfulness also extends to all my fellow postgraduate colleagues. Thank you for all your views, comments, and critics. Their support and assistance towards completing this thesis should be recognized. Unfortunately, it is impossible to list all of them in this limited space. Finally, thanks to all those who directly or indirectly had help in making this thesis a success. Your support and help are momentous for me.

ABSTRACT

Bleaching earth and citric acid are expensive chemicals utilized in the palm oil refining process. Both chemicals are important in removing impurities such as colour pigments and other breakdown products in crude palm oil. The purpose of this study was to successfully develop refined oil quality prediction model and to optimize the dosage of bleaching earth and citric acid utilized in a palm oil refining process. First, response surface methodology (RSM) was used to develop an empirical model to relate the removal rate of free fatty acid (FFA) and red colour pigments in the refined oil to the dosage of both bleaching earth and citric acid. Next, artificial neural networks (ANNs) models were developed based on the pilot-scale experimental data and actual palm oil refining plant data as input and output data for the models. The quality parameters of crude oil (FFA and colour pigment content) as well as process parameters (bleaching earth and citric acid dosage, pressure and temperature of the deodorizer) were the input data while the quality of refined oil (FFA and red colour pigments content) were the output data. For comparison purpose, three types of ANN models were developed, which were multi-layer perceptron (MLP), stacked neural network (SNN) models and radial basis function neural network (RBFNN) models. All the ANN models developed were able to predict the quality of the refined palm oil. The developed models were compared and the best model, the SNN model, was chosen as the model for refined palm oil quality prediction. Finally, optimization frameworks to optimize the palm oil refining process were developed based on the multi-objective genetic algorithms approach using RSM and ANN models. The RSM models were validated by comparing the predicted value with the actual pilot-scale data, while all ANN models were validated by a new set of actual palm oil refining plant data. From the findings, bleaching earth dosage was found to be the major contributor to the impurities removal rate affecting the palm oil refining performance. Optimizing the dosage of bleaching earth and citric acid enabled significant savings in raw material usage, thus creating a more sustainable and cost-effective palm oil refining process. The models developed from this study were able to predict the quality of the refined oil accurately and quickly, gave the optimum dosage of the bleaching earth and citric acid, as well as provided optimum point of pressure and temperature of the deodorization process.

ABSTRAK

Tanah peluntur dan asid sitrik adalah bahan kimia mahal yang digunakan dalam proses penapisan minyak sawit. Kedua-dua bahan kimia ini penting dalam menyingkirkan bendasing seperti pigmen warna dan produk terpisah lain dalam minyak sawit mentah. Tujuan kajian ini adalah untuk membangunkan model bagi meramalkan kualiti minyak bertapis dan mengoptimumkan dos tanah peluntur dan asid sitrik yang digunakan dalam proses penapisan minyak sawit. Pertama, kaedah gerakbalas permukaan (RSM) digunakan untuk membangunkan model empirikal untuk mengaitkan kadar penyingkiran asid lemak bebas (FFA) dan kandungan pigmen warna merah dalam minyak bertapis dengan dos kedua-dua tanah peluntur dan asid sitrik. Seterusnya, model rangkaian saraf tiruan (ANN) dibangunkan berdasarkan data skala perintis dan data dari kilang pemprosesan minyak sawit sebenar sebagai data masuk dan data keluar model tersebut. Kualiti minyak mentah (FFA dan kandungan pigmen warna) serta parameter proses (dos tanah peluntur dan asid sitrik, tekanan dan suhu penyahbau) adalah data masuk sementara kualiti minyak bertapis (FFA dan kandungan pigmen merah) adalah data keluar. Untuk tujuan perbandingan, tiga jenis model ANN dibangunkan, yang terdiri daripada model *perceptron* pelbagai lapisan (MLP), model rangkaian neural bertindan (SNN) dan model rangkaian neural fungsi berdasar radial (RBFNN). Semua model ANN yang dibangunkan dapat meramalkan kualiti minyak sawit bertapis. Model-model yang dibangunkan dibandingkan, dan model terbaik, model SNN dipilih sebagai model bagi meramalkan kualiti minyak sawit bertapis. Akhirnya, kerangka pengoptimuman untuk mengoptimumkan proses penapisan minyak sawit dibangunkan berdasarkan pendekatan algoritma genetik pelbagai objektif menggunakan model RSM dan ANN. Model RSM disahkan dengan membandingkan nilai yang diramalkan dengan data sebenar skala perintis manakala semua model ANN disahkan menggunakan kumpulan data baharu dari kilang penapisan minyak sawit sebenar. Dari dapatan kajian, didapati dos tanah peluntur menjadi penyumbang utama kadar penyingkiran bendasing yang mempengaruhi prestasi proses penapisan minyak sawit. Mengoptimumkan dos tanah peluntur dan asid sitrik dapat mewujudkan penjimatan besar dalam penggunaan bahan mentah dan menghasilkan proses penapisan minyak sawit mentah yang lestari dan menjimatkan kos. Model yang dibangunkan dari kajian ini dapat meramalkan kualiti minyak sawit bertapis dengan tepat dan pantas, dapat memberikan dos optimum tanah peluntur dan asid sitrik, serta memberikan titik optimum bagi tekanan dan suhu proses penyahbauan.

TABLE OF CONTENTS

	TITLE	PAGE
DECLARATI	ON	iii
DEDICATION	J	iv
ACKNOWLE	DGEMENT	v
ABSTRACT		vi
ABSTRAK		vii
TABLE OF C	ONTENTS	viii
LIST OF TAB	LES	xii
LIST OF FIG	URES	xiv
LIST OF ABB	REVIATIONS	xvii
LIST OF SYM	IBOLS	XX
LIST OF APP	ENDICES	xxii
CHAPTER 1	INTRODUCTION	1
1.1	Introduction	1
1.2	Research Background	2
1.3	Problem Statement	4
1.4	Objective of the Research	5
1.5	Scope of the Study	6
1.6	Research Contributions	7
1.7	Thesis Outline	8
CHAPTER 2	LITERATURE REVIEW	9
2.1	Introduction	9
2.2	Palm Oil Refining Process	9
2.3	Process Modelling	11
2.4	Response Surface Methodology	13
2.5	Artificial Neural Network Modelling	15
2.6	Optimization	19
2.7	Summary of Research Gap	21

CHAPTER 3	METHODOLOGY				
3.1	Introduction				
3.2	Process Description				
3.3	Experimental Data Collection	29			
	3.3.1 Design of Experiment (DOE)	29			
	3.3.2 Experimental Materials and Procedure	32			
3.4	Chemical Analysis of Palm Oil	34			
	3.4.1 Determination of Free Fatty Acids Content	34			
	3.4.2 Determination of Colour	35			
3.5	Palm Oil Refinery Plant Data Collection	36			
3.6	Response Surface Correlation Development	37			
	3.6.1 Correlation Fitting	38			
	3.6.2 Analysis of Variance (ANOVA)	39			
	3.6.3 Re-Fitting and Regression Analysis	40			
	3.6.4 Response Surface and Contour Plots	40			
	3.6.5 Prediction	41			
	3.6.6 Validation	41			
3.7	Artificial Neural Network Model Development	42			
	3.7.1 Multi-Layer Perceptron Neural Network Model	46			
	3.7.2 Stacked Neural Network Model	48			
	3.7.3 Radial Basis Function Neural Network Model	49			
	3.7.4 Model Comparison and Selection	50			
	3.7.5 Sensitivity Analysis	50			
	3.7.6 Model Validation	51			
3.8	Optimization	52			
	3.8.1 Single Objective Optimization Development	52			
	3.8.2 Multi-Objective Genetic Algorithms (MOGA) Optimization Development	53			
	3.8.2.1 RSM-MOGA Mathematical Formulation	55			
	3.8.2.2 ANN-MOGA Mathematical Formulation	56			
3.9	Summary of Methodology Developed				

CHAPTER 4	RESU	ULTS AN	ND DISCUSSION	59	
4.1	Introduction				
4.2	Respo	nse Surfa	ace Correlation	59	
	4.2.1	Result	and Discussion	60	
		4.2.1.1	RSM Correlation Fitting	60	
		4.2.1.2	ANOVA and Regression Analysis	61	
		4.2.1.3	Response Surface and Contour Plots	64	
		4.2.1.4	RSM Prediction	68	
	4.2.2	Validat	ion	73	
4.3	Artific	cial Neur	al Network Model	74	
	4.3.1	Result	and Discussion	75	
		4.3.1.1	Multi-Layer Perceptron Neural Network Model	75	
		4.3.1.2	Stacked Neural Network Model	81	
		4.3.1.3	Radial Basis Function Neural Network Model	83	
	4.3.2	Overall	ANN Model Comparison	84	
	4.3.3	Model	Improvement	89	
	4.3.4	Sensitiv	vity Analysis	91	
	4.3.5	Model	Validation	93	
4.4	Optim	ization F	Framework	94	
	4.4.1	Respon	se Surface Optimization	94	
		4.4.1.1	Single Objective Optimization	94	
		4.4.1.2	Hybrid RSM-MOGA Optimization Framework	95	
	4.4.2	Hybrid	ANN-MOGA Optimization Framework	99	
4.5	Summ	ary of R	esults	103	
CHAPTER 5	CON	CLUSIO	NS AND RECOMMENDATIONS	105	
5.1	Introd	uction		105	
5.2	Concl	usions		105	
	5.2.1	Respon	se Surface Correlation	105	
	5.2.2	Artifici	al Neural Network Model	106	
	5.2.3	Optimi	zation Framework	108	
5.3	Recommendations				

LIST OF TABLES

TABLE NO.	TITLE	PAGE
3.1	The actual and coded levels of factors	31
3.2	The optimal set of runs generated by the D-Optimal design	31
3.3	List of input variables	37
3.4	List of output variables	37
3.5	List of the developed ANN models	46
3.6	The Multi-Objective Genetic Algorithms settings	55
4.1	The ANOVA result of RSM correlations	60
4.2	The ANOVA result for the re-fitted RSM correlations	61
4.3	The regression test result of RSM correlations	63
4.4	The list of the experimental data, the RSM prediction and absolute error	69
4.5	The list of the actual plant data and the RSM prediction	73
4.6	The correlation coefficient and MSE value for training, validation, testing, and overall model for ANN-3 models	80
4.7	The correlation coefficient and MSE value for training, validation, testing, and overall model for ANN-4 model	82
4.8	The correlation coefficient and MSE value for training, validation, testing, and overall model for ANN-5 model	84
4.9	The Correlation coefficient (R) and MSE for all ANN models	87
4.10	The Correlation coefficient (R) and MSE for ANN-4 and ANN-4.2	90
4.11	The optimum values of independent variables for each framework	95
4.12	The Optimal Values (OV) obtained by Multi-Objective Genetic Algorithm (MOGA)	97
4.13	The comparison between single-objective and multi- objective optimization	98

4.14	The R-Value and MSE of the training, validation, testing and overall model		
4.15	The optimal solutions obtained using ANN-MOGA	101	

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
1.1	The palm oil physical refining process	3
2.1	The working principle of the artificial neural network	15
3.1	The overall research methodology	24
3.2	The actual palm oil refining plant process	28
3.3	The design of the experiment flowchart	30
3.4	The experimental setup for the combined degumming and bleaching	33
3.5	The Lovibond Tintometer colorimeter	35
3.6	The response surface methodology step	38
3.7	The artificial neural network modelling step	43
3.8	The architecture of the ANN-1 and ANN-2	47
3.9	The architecture of the ANN-3A and ANN-3B model	48
3.10	The architecture of the ANN-3C model	48
3.11	The architecture of the ANN-4 model	49
3.12	The block diagram of the Multi-Objective Genetic Algorithms	54
3.13	The best structure of ANN model for ANN-MOGA	57
4.1	The response surface and contour plot for FFA removal percentage of CPKOL oil	64
4.2	The response surface and contour plot for red colour pigments removal percentage of CPKOL oil	65

4.3	The response surface and contour plot for FFA removal percentage of CPKST oil	66
4.4.	The response surface and contour plot for red colour pigments removal percentage of CPKST oil	67
4.5	The FFA removal percentage between experimental and predicted responses	70
4.6	The red colour pigments removal percentage between experimental and predicted responses	71
4.7	The absolute error profile between experimental data and RSM prediction	72
4.8	The absolute error profile between actual plant data and RSM prediction	74
4.9	The effect of the number of hidden nodes on ANN-1 model	75
4.10	The best architecture for the ANN-1 model	76
4.11	The effect of the number of hidden nodes on ANN-2 Model	77
4.12	The best architecture for the ANN-2 model	77
4.13	Best Architecture for ANN-3A and ANN-3B	78
4.14	The actual data versus ANN predicted values for the ANN-3C model	79
4.15	The structure of ANN-4 model	81
4.16	The actual data versus ANN predicted values for the ANN-4 model	82
4.17	The structure of the ANN-5 model	83
4.18	The actual data, ANN-1 prediction, and RSM prediction for FFA removal rate of CPKOL oil	85
4.19	The actual data, ANN-1 prediction, and RSM prediction for red colour removal rate of CPKOL oil	85
4.20	The actual data, ANN-2 prediction, and RSM prediction for FFA removal rate of CPKST oil	86

4.21	The actual data, ANN-2 prediction, and RSM prediction for red colour removal rate of CPKST oil	86
4.22	The effect of the number of hidden nodes of the R-value and MSE on ANN models	88
4.23	The effect of the number of hidden nodes on the MSE of ANN models	89
4.24	The effect of the number of hidden nodes on the R-value and MSE on ANN-4.2 model	90
4.25	The results of the sensitivity analysis	91
4.26	The R and MSE value of ANN validation models	93
4.27	The Pareto front graph for RSM-MOGA-1	96
4.28	The Pareto front graph for RSM-MOGA-2	96
4.29	The best ANN network model for ANN-MOGA	100
4.30	The Pareto front for ANN-MOGA model	101

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
AOCS	-	American Oil Chemists' Society
AV	-	Acid Value
BDPKOL	-	Bleached and Degummed Palm Kernel Olein
BE	-	Bleaching Earth
BP	-	Back Propagation
CA	-	Citric Acid
CCD	-	Central Composite Design
CCRD	-	Central Composite Rotatable Design
CIQ	-	China's Inspection and Quarantine Bureau
СРО	-	Crude Palm Oil
СРКО	-	Crude Palm Kernel Oil
CPKOL	-	Crude Palm Kernel Olein
CPKST	-	Crude Palm Kernel Stearin
DOE	-	Design of Experiment
FFA	-	Free Fatty Acids
GA	-	Genetic Algorithms
IV	-	Iodine Value
КОН	-	Potassium Hydroxide
MCPD	-	Mono-chloropropane-diol
MD	-	Molecular Distillation
MEOMA	-	Malayan Edible Oil Manufacturers' Association
MISO	-	Multiple Input Single Output

MIMO	-	Multiple Inputs Multiple Outputs
MLP	-	Multi-layer Perceptron
MSE	-	Mean Square Error
MOGA	-	Multi-Objective Genetic Algorithms
MOO	-	Multi-Objective Optimization
MPOB	-	Malaysian Palm Oil Board
NADES	-	Natural Deep Eutectic Solvent
NSGA-II	-	Non-dominated Sorting Algorithm II
O/S	-	Oil Surfactant
OSI	-	Oil Stability Index
paV	-	p-anisidine
PE	-	Processing Element
PCR	-	Principal Component Regression
PKOL	-	Palm Kernel Olein
PKST	-	Palm Kernel Stearin
PO	-	Palm Oil
PORAM	-	Palm Oil Refiners Association of Malaysia
PORIM	-	Palm Oil Research Institute of Malaysia
PV	-	Peroxide Value
R	-	Correlation Coefficient
RBDPO	-	Refined Bleached and Deodorized Palm Oil
RBF	-	Radial Basis Function
RBFNN	-	Radial Basis Function Neural Network
RMSE	-	RMSE Root Mean Square Error
RPO	-	Refined Palm Oil
RPKO	-	Refined Palm Kernel Oil
RS	-	Response Surface

RSM	-	Response Surface Metholody
SBE	-	Spent Bleaching Earth
SFE	-	Supercritical Fluid Extraction
SNN	-	Stacked Neural Network
USDA	-	United States Department of Agriculture

LIST OF SYMBOLS

\mathbb{R}^2	-	Regression
R	-	Correlation coefficients
β_n	-	Regression coefficients
Y _i	-	Response variable
X _n	-	Independent variable
newff	-	Feed forward network
tansig	-	Tangent sigmoid transfer function
logsig	-	Log-sigmoid transfer function
purelin	-	Linear transfer function
trainlm	-	Levenberg-Marquardt learning algorithms
radbas	-	Radial basis transfer function
Error _i	-	Error of network without one variable
W	-	Quotient W of sensitivity analysis
\mathbf{W}_{n}	-	Weights of neural network
bn	-	Biases of neural network
Xi	-	Value of variable-x
y _i	-	Value of variable-y
x	-	Mean of variable-x
\overline{y}	-	Mean of variable-y
N _{pop}	-	N population
Nelite	-	N elite population
Deo-P	-	Deodorizer pressure
Deo-T	-	Deodorizer temperature
w/w	-	Weight / weight (percentage)

RY	-	Red:Yellow colour ratio
gm	-	Gram
mL	-	millilitre
М	-	Molar
S	-	Second
e	-	Exponential
р	-	Probability value
3-D	-	Three-dimensional
2-D	-	Two-dimensional

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
А	Experimental Data and Plant Data	125
В	Coding Program using MATLAB 2015b	131
С	Overall Result of R-value and MSE for Training, Testing, Validation, and Overall Model of all ANN	145
D	Weights and biases of ANN-3 Model for ANN-4 Model	151
Е	ANN-MOGA Model Equation	154
F	Weights and biases for ANN-MOGA Model	155

CHAPTER 1

INTRODUCTION

1.1 Introduction

Elaeis guineensis, famously known as palm oil, is vegetable oil from the oil palm tree's fruit. The oils extracted from palm oil fresh fruit bunch may exist in two types; Palm Oil (PO) and Palm Kernel Oil (PKO). With a total yield of ~4 tons of PO and PKO per hectare per year, palm oil is the most productive oil crop globally, which is ten times more productive than soybean oils (Malaysian Palm Oil Council, 2020). From 1980, palm oil has become the world's second most crucial vegetable oil after soybean oil (Sambanthamurthi, 2000). The National Commodities Policy (NCP) 2011-2020 was formulated by Malaysian government to guide the Malaysian palm oil industry. A recent United States Department of Agriculture (USDA) report proved that palm oil is currently the world's main vegetable oil that counts 39 % of the total vegetable oils. Malaysia is the world's second-largest producer of palm oil (United States Department of Agriculture (USDA), 2020). Palm oil is not only used as frying oil but also commonly used in the food processing industry to produce margarine, spreads, bread, cookies, cakes, filling creams, ice-creams, and non-dairy whipping creams and chocolate. Palm oil is widely used in frying fast food and manufacturing food products such as crisps, instant noodles, and infant formula. Other than the food industry, palm oil is also widely used in numerous other daily products such as soaps, cosmetics, and biofuel. Being the world's most versatile raw materials result in a rise in worldwide demand for palm oil since the 1980s.

This chapter gives a summary of palm oil production worldwide. Next, the research background and a problem statement will be described. This study's research objectives and scope relevant to the process modelling and optimization of the palm oil refining process are explained afterwards. Lastly, this chapter emphasizes this work's contributions regarding refined palm oil's quality prediction and process optimization.

1.2 Research Background

Crude Palm Oil (CPO) contains complex mixtures of majorly triacylglycerols (TAGs), and minorly monoacylgylcerol and diacylglycerol. These type of TAGs is depend on the components of the fatty acid in the TAGs. Fatty acids in oil palm generally contain 50 % saturated fatty acids, 40% monounsaturated fatty acids, and 10% polyunsaturated fatty acids. Each palm oil (palm oil, palm olein and palm stearin) can be differentiated using their palmitic acid proportions in the fatty acids. Other minor components in palm oil include Free Fatty Acids (FFAs), carotene, tocopherols, tocotrienols, phytosterols, moisture and impurities, sterols, phospholipids, glycolipids, and terpenic and paraffinic hydrocarbons (Goh et al., 1985; Tan and Nehdi, 2012).

FFAs can be increased by enzymes and microbial lipase in the palm fruit, resulting in a high level of FFAs in CPO. During storage, the oil reaction with water will produce FFAs, increasing the crude oil's FFAs content (Che Man et al., 1999). Consequently, the high level of FFAs (exceeding 5% of the standard requirement of FFA in CPO) makes it unhealthy for human consumption (Japir et al., 2017). Moreover, high carotene content in CPO results in a deep orange-red colour of the oil, while most consumers favoured light-coloured oil. Also, the high level of carotene in palm oil affects its oxidative stability (Tan and Nehdi, 2012). Besides, improper bleaching and degumming process will result in a poor quality of refined palm oil's colour, which is called colour reversion (Gibon, 2012). In short, these two undesired components of palm oil need to be lowered to a specific level by the refining process. Palm oil can be refined through a chemical or physical refining process (Ceriani and Meirelles, 2006; Gibon et al., 2007). Physical refining is more favoured than chemical refining because it is more suitable for producing edible oil and more environmentally friendly than chemical refining (Yang et al., 2008).



Figure 1.1 The palm oil physical refining process

Figure 1.1 illustrates the overall palm oil physical refining process. The degumming process involved the treatment of crude oil with a dilute acid such as phosphoric or citric acid, while the bleaching is a decolourization process in which the degummed oil is treated with special adsorbents (bleaching earth). Combining both processes improved the quality of the degummed and bleached oil. (Čmolík and Pokorný, 2000). Deodorization is the final palm oil refining process where the FFA, odour, flavour, and some colour pigment, and any other volatile minor undesired particles are removed from the CPO or CPKO by vacuum stripped method operated at high temperature (220°C-260°C).

The product quality in the palm oil refinery plant process is very crucial and essential to be taken care of. According to current practice in palm oil refinery plant, FFA content, colour, Iodine Value (IV), and moisture content are the major quality parameters. The specifications need to be accurately followed, or else the refined palm oil will be classified as an off-specification product. China, as the second-largest palm oil importer, had tightened the requirement on the quality of imported Refined Palm Oil (RPO). This results in theslow down on palm oil's demand and dropping the crude palm oil price.(*TheStar*, 2014). The new "landed quality" which are the new quality standard of the imported palm oil that has been introduced by China's Inspection and Quarantine Bureau's (CIQ) will make the off-specification RPO be rejected and not allowed to be re-refined in China (Adnan, 2013). Malaysian Palm Oil Board (MPOB)

said that about 5% of the exported palm oil did not fulfil the new CIQ specifications in 2013, representing approximately 175 000 tons of palm oil. The palm oil refinery plant in Malaysia needs to control their RPO quality to avoid the risk of rejection. Thus, there is a need for improvement in the current operation of the palm oil refining industry.

1.3 Problem Statement

The fourth industrial revolution (IR 4.0) is the new growing trend towards automation and digitalization of industry. IR 4.0 includes the cyber-physical system, the Industrial Internet of Things (IIoT), and cognitive computing based on Artificial Intelligence (AI). Unfortunately, the palm oil industry has been moving slowly in this revolution. Currently, there is no automatic sensor for quality prediction in the palm oil refining process. The plant operator manually collects the refined oil sample, and its quality is manually check in the laboratory, which is time-consuming.

Also, in the current palm oil refining industry, the raw material dosage of bleaching earth and the citric dosage depends on the plant's operators' decision. From the observation made in the refinery plant and interview with the plant's expert, the main qualities focused by the palm oil refinery plant is the FFA content and colour of the refined oil. These qualities are checked several times throughout the refining process, especially after the combined degumming and bleaching process. The oil will be on-hold while the plant's operator sent the oil sample to the chemical laboratory. The oil will be sent out to the filtration process only after the quality of the FFA and colour is confirmed. If the quality does not meet the minimum specification, extra dosage of the bleaching earth and citric acid will be added to the process. This will increase the operating cost, and thus, a quality prediction model will be a good solution to this situation.

In line with IR 4.0, adopting digitalization tools in the palm oil refining industry for better decision-making will increase productivity and reduce operating costs. Therefore, there is a need to model the refined palm oil quality and optimize the palm oil refining industry's process parameters. The palm oil refining process's modelling is very difficult due to palm oil's complex chemical components. The quality of the crude palm oil varies as the chemical components vary. This complexity of chemical components in palm oil makes the first principal modelling of the palm oil refining process a difficult task to be accomplished. Thus, black-box modelling is a better choice in modelling of palm oil refining process.

Few literatures related to the modelling and optimization of the palm oil refinery plant process has been found. The application of RSM in palm oil refining was explored by Zulkurnain et al. (2013) in a specific modified refining process and by Ceriani et al. (2010) in a specific thin-film deodorizer simulation. The D-Optimal design in RSM application for palm oil refining has not been explored. The D-Optimal design is a straight optimization of number of run of an experiment where the optimality criterion and the model will be fixed. Besides, the application of the ANN in the palm oil refining process is focused on the specific Molecular Distillation (MD) process (Tehlah, 2016) and in predicting dosage of phosphoric acid and bleaching earth in experimental combined degumming and bleaching process (Morad et al., 2010). There is no application of ANN that utilize the real plant data found so far. Also, no literature on the hybrid method of RSM with Multi-Objective Genetic Algorithms (MOGA) and hybrid method of ANN with MOGA in the palm oil refinery industry was found. The MOGA method is an ideal method in solving multi-objective problems where it can find multiple optimal solution in one single simulation run. Therefore, the application of MOGA method in palm oil refining proces should be explored.

1.4 Objective of the Research

This research aims to develop a palm oil refining model integrating refined palm oil quality prediction and process parameter optimization. The objective is fulfilled through the Response Surface Methodology (RSM), Artificial Neural Network (ANN), and Multi-Objective Genetic Algorithms (MOGA) method. The details of the objective are as follows:

- 1. To develop empirical model of the combined degumming and bleaching process using Response Surface methodology (RSM) method.
- 2. To develop a quality prediction model of refined palm oil using experimental data and actual plant data utilizing the ANN model that represent the actual palm oil refinery plant process.
- 3. To optimise the palm oil refining process by minimizing the usage of raw material and maximizing the final quality of the palm oil refinery product.

1.5 Scope of the Study

The scope of the research is divided to two parts: pilot-scale plant and actual refinery plant. For pilot-scale plant,

- i. The process is focused only on the combined degumming and bleaching process, without deodorization process. This is due to the limitation in accessibility of equipment by the plant.
- ii. The research is limited only at the pilot-scale plant of the specific palm oil plant.
- iii. The research focused only on two types of palm oil which are Crude Palm Kernel Olein (CPKOL) and Crude Palm Kernel Stearin (CPKST).
- iv. The data from this pilot-scale plant experiment were used in developing correlation equations between process variables and removal rate of the impurities in the oil by utilizing RSM.
- v. The developed correlation equations were then employed in optimizing the process variables.

For palm oil actual plant,

- i. The process involved overall refining process which are the combined degumming and bleaching and the deodorization process.
- ii. The data consist of variety types of oil such as CPKST, CPKOL, Crude Palm Oil (CPO), Crude Palm Kernel Oil (CPKO) and others. This is according to the type of oil run in a specific production date of the palm oil refinery plant.
- iii. The overall process is based on the specific palm oil refinery plant only.

iv. The data from the actual refinery plant were used to model quality estimation model utilizing ANN.

The correlation by RSM using pilot-scale data and the ANN model utilizing the actual plant data have been programmed into MATLAB R2015b environment.

1.6 Research Contributions

This study fills the research gap in process modelling and optimization of palm oil refining. The existing research in palm oil modelling used simulation data obtained from simulation programs that do not fully represent the actual palm oil refining process in an actual refinery plant. Besides, the types of ANN that best represents the palm oil refining process have not been explored. The contributions of the thesis are enlightened below:

- Quality estimation model based regression correlation based on RSM for utilizing pilot-scale plant data and an ANN model based on actual palm oil refining plant data were developed and shown to be viable for implementation in a real palm oil refining plant as a quality prediction sensor.
- 2. Optimization of the refined palm oil quality that minimizes the raw material usage while keeping the quality within the desired range by utilizing the hybrid RSM-MOGA and hybrid ANN-MOGA approach.
- 3. The optimum value obtained from this research can serve as a starting point in real palm oil refining plant optimization.
- 4. The methods used in this study which are hybrid RSM-MOGA and ANN-MOGA can serve as guideline in optimization of palm oil refining plant.

1.7 Thesis Outline

This thesis consists of five chapters and organized as follows:

Chapter 1 introduces the background of the study, problem statement, objective, research scope and significance of the research.

Chapter 2 covers the literature review and research gaps in the modelling and optimization of palm oil refining. The previous research on the process modelling of palm oil refining, RSM and ANN modelling in palm oil refining and palm oil refining optimization are reviewed.

Chapter 3 explains the detailed methodology of this research to fulfill the presented objectives. This chapter includes the data collection method in experimental work and actual refinery plant, development of process modelling of palm oil refining using RSM and ANN, and finally, the development of the optimization of palm oil refining process.

Chapter 4 describes the results from the RSM correlation, ANN modelling, and the hybrid RSM-MOGA and ANN-MOGA optimization frameworks and thoroughly discusses the fulfilled objectives.

Chapter 5 integrates the conclusions gained from the research done and some recommendations for future studies.

REFERENCES

- Ajala, S. O. and Alexander, M. L. (2020). Multi-objective optimization studies of microalgae dewatering by utilizing bio-based alkali: a case study of response surface methodology (RSM) and genetic algorithm (GA). SN Applied Sciences, 2(3), 387.
- Abdullah, S. and Tiong, E. C. (2008). Prediction of palm oil properties using artificial neural network. *International Journal of Computer Science and Network Security*, 8(8), 101-106.
- Adnan H., 2013, China's tighter rules may hurt palm oil industry, The Star, Kuala Lumpur, Malaysia.
- Agatonovic-Kustrin, S. and Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of Pharmaceutical and Biomedical Analysis*, 22(5), 717-727.
- Ahmad, A., Azid, I., Yusof, A. and Seetharamu, K. (2004). Emission control in palm oil mills using artificial neural network and genetic algorithm. *Computers & Chemical Engineering*, 28(12), 2709-2715.
- Aini, H. and Haviluddin, H. (2019). Crude Palm Oil Prediction Based on Backpropagation Neural Network Approach. *Knowledge Engineering and Data Science*, 2(1), 1-9.
- Alhammadi, H. Y. and Romagnoli, J. A. (2004). Chapter B4 Process design and operation: Incorporating environmental, profitability, heat integration and controllability considerations. In P. Seferlis and M. C. Georgiadis (Eds.), *Computer Aided Chemical Engineering* (Vol. 17, pp. 264-305): Elsevier.
- Ali, N. S., Mohd-Yusof, K., Othman, M. F., Latip, R. A. and Ismail, M. S. N. (2019). Adaptive Neuro Fuzzy Inference System (ANFIS) modelling for quality estimation in palm oil refining process. J. Mech. Eng., 8(1), 36-47.
- Al-Zahrani, A. and Daous, M. (2000). Recycling of spent bleaching clay and oil recovery. *Process Safety and Environmental Protection*, 3(78), 224-228.
- Amelia, L., Wahab, D. A. and Hassan, A. (2009). Modelling of palm oil production using fuzzy expert system. *Expert Syst. Appl.*, 36(5), 8735–8749.
- American Oil Chemists' Society (AOCS) (1998) Official methods and recommended practices of the American Oil Chemists' Society, 5th edn. Champaign, Illinois.

- Aydar, A. Y. (2018). Utilization of response surface methodology in optimization of extraction of plant materials. *Statistical approaches with emphasis on design of experiments applied to chemical processes*, 157-169.
- Bagheri, M., Mirbagheri, S. A., Ehteshami, M. and Bagheri, Z. (2015). Modeling of a sequencing batch reactor treating municipal wastewater using multi-layer perceptron and radial basis function artificial neural networks. *Process Safety* and Environmental Protection, 93, 111-123.
- Bahadi, M., Yusoff, M., Salimon, J. and Derawi, D. (2020). Optimization of Response Surface Methodology by D-Optimal Design for Alkaline Hydrolysis of Crude Palm Kernel Oil. Sains Malaysiana, 49, 29-41.
- Bala, K. L., Broadway, A. and Kumar, A. (2019). Identification process parameters for refining of wild walnut (Juglans regia L.) Heijuga oil of Manipur, India using response surface methodology (RSM).
- Banerjee, A., Guria, C. and Maiti, S. K. (2016). Fertilizer assisted optimal cultivation of microalgae using response surface method and genetic algorithm for biofuel feedstock. *Energy*, 115, 1272-1290.
- Basiron, Y., Palm Oil, in: Shahidi, F. (Ed.), Bailey's Industrial Oil and Fat Products,6 ed. John Wiley & Sons, Inc., (2005), pp. 333 429.
- Basri, M., Rahman, R. N. Z. R. A., Ebrahimpour, A., Salleh, A. B., Gunawan, E. R. and Rahman, M. B. A. (2007). Comparison of estimation capabilities of response surface methodology (RSM) with artificial neural network (ANN) in lipase-catalyzed synthesis of palm-based wax ester. *BMC Biotechnology*, 7(1), 53.
- Betiku, E., Odude, V. O., Ishola, N. B., Bamimore, A., Osunleke, A. S. and Okeleye,
 A. A. (2016). Predictive capability evaluation of RSM, ANFIS and ANN: A case of reduction of high free fatty acid of palm kernel oil via esterification process. *Energy Conversion and Management*, 124, 219-230.
- Bezerra, M. A., Santelli, R. E., Oliveira, E. P., Villar, L. S. and Escaleira, L. A. (2008). Response surface methodology (RSM) as a tool for optimization in analytical chemistry. *Talanta*, 76(5), 965-977.
- Biegler, L. T. and Grossmann, I. E. (2004). Retrospective on optimization. *Computers & Chemical Engineering*, 28(8), 1169-1192.

- Cao, X., Jia, S., Luo, Y., Yuan, X., Qi, Z. and Yu, K.-T. (2019). Multi-objective optimization method for enhancing chemical reaction process. *Chemical Engineering Science*, 195, 494-506.
- Cardoso, J. M. P., Coutinho, J. G. F. and Diniz, P. C. (2017). Chapter 8 Additional topics. In J. M. P. Cardoso, J. G. F. Coutinho and P. C. Diniz (Eds.), *Embedded Computing for High Performance* (pp. 255-280). Boston: Morgan Kaufmann.
- Ceriani, R. and Meirelles, A. J. A. (2006). Simulation of continuous physical refiners for edible oil deacidification. *Journal of food engineering.*, *76*(3), 261-271.
- Ceriani, R., Meirelles, A. J. A. and Gani, R. (2010). Simulation of thin-film deodorizers in palm oil refining. *Journal of Food Process Engineering*, 33(suppl. 1), 208-225.
- Chatterjee, S., Sarkar, S., Dey, N., Sen, S., Goto, T. and Debnath, N. C. (2017, 24-26 July 2017). Water quality prediction: Multi objective genetic algorithm coupled artificial neural network based approach. Paper presented at the 2017 IEEE 15th International Conference on Industrial Informatics (INDIN).
- Chelladurai, S. J. S., K, M., Ray, A. P., Upadhyaya, M., Narasimharaj, V. and S, G. (2020). Optimization of process parameters using response surface methodology: A review. *Materials Today: Proceedings*.
- Che Man, Y. B., Moh, M. H. and van de Voort, F. R. (1999). Determination of free fatty acids in crude palm oil and refined-bleached-deodorized palm olein using fourier transform infrared spectroscopy. Journal of the American Oil Chemists' Society, 76(4), 485–490.
- Chen, Q., Bi, J., Zhou, Y., Liu, X., Wu, X. and Chen, R. (2014). Multi-objective Optimization of Spray Drying of Jujube (Zizyphus jujuba Miller) Powder Using Response Surface Methodology. *Food and Bioprocess Technology*, 7(6), 1807-1818.
- Cheng, F. Y. (1999). Multiobjective Optimum Design of Structures with Genetic Algorithm and Game Theory: Application to Life-Cycle Cost Design. In F. Y. Cheng and Y. Gu (Eds.), *Computational Mechanics in Structural Engineering* (pp. 1-16). Oxford: Elsevier Science Ltd.
- Chew, S. C., Tan, C. P. and Nyam, K. L. (2017). Optimization of degumming parameters in chemical refining process to reduce phosphorus contents in kenaf seed oil. *Separation and Purification Technology*, 188, 379-385.

- Chew, S. C., Tan, C. P. and Nyam, K. L. (2017). Optimization of Bleaching Parameters in Refining Process of Kenaf Seed Oil with a Central Composite Design Model. *Journal of food science*, 82(7), 1622-1630.
- Chew, S.-C., Tan, C.-P. and Nyam, K.-L. (2017). Application of response surface methodology for optimizing the deodorization parameters in chemical refining of kenaf seed oil. *Separation and Purification Technology*, *184*, 144-151.
- Čmolík, J. and Pokorný, J. (2000). Physical refining of edible oils. *European journal* of lipid science and technology, 102(7), 472-486.
- Darajeh, N., Idris, A., Fard Masoumi, H. R., Nourani, A., Truong, P. and Rezania, S. (2017). Phytoremediation of palm oil mill secondary effluent (POMSE) by Chrysopogon zizanioides (L.) using artificial neural networks. *International Journal of Phytoremediation*, 19(5), 413-424.
- Darvishi, H., Farhudi, Z. and Behroozi-Khazaei, N. (2020). Multi-objective optimization of savory leaves drying in continuous infrared-hot air dryer by response surface methodology and desirability function. *Computers and Electronics in Agriculture, 168*, 105112.
- de França, L. F. and Meireles, M. A. A. (2000). Modeling the extraction of carotene and lipids from pressed palm oil (Elaes guineensis) fibers using supercritical CO2. *The Journal of Supercritical Fluids*, 18(1), 35-47.
- Demissie, A., Zhu, W. and Belachew, C. T. (2017). A multi-objective optimization model for gas pipeline operations. *Computers & Chemical Engineering*, 100, 94-103.
- do Prado, A. C. P., & Block, J. M. (2012). 9 Palm and Palm Kernel Oil Production and Processing in Brazil. In O.-M. Lai, C.-P. Tan, & C. C. Akoh (Eds.), *Palm Oil* (pp. 251-274): AOCS Press.
- Eesa, A. and Arabo, W. (2017). A Normalization Methods for Backpropagation: A Comparative Study. Science Journal of University of Zakho, 5, 319.
- Fact Sheets Malaysian Palm Oil. (2020). In. National Library of Malaysia: Malaysian Palm Oil Board and Malaysian Palm Oil Council.
- Farhoosh, R., Einafshar, S. and Sharayei, P. (2009). The effect of commercial refining steps on the rancidity measures of soybean and canola oils. *Food Chemistry*, 115(3), 933-938.

- Farsi, A., Dincer, I. and Naterer, G. F. (2020). Multi-objective optimization of an experimental integrated thermochemical cycle of hydrogen production with an artificial neural network. *International Journal of Hydrogen Energy*, 45(46), 24355-24369.
- Franke, K., Strijowski, U., Fleck, G. and Pudel, F. (2009). Influence of chemical refining process and oil type on bound 3-chloro-1, 2-propanediol contents in palm oil and rapeseed oil. *LWT-Food Science and Technology*, 42(10), 1751-1754.
- Furtuna, R., Curteanu, S. and Leon, F. (2011). An elitist non-dominated sorting genetic algorithm enhanced with a neural network applied to the multi-objective optimization of a polysiloxane synthesis process. *Engineering Applications of Artificial Intelligence*, 24(5), 772-785.
- Furtuna, R., Curteanu, S. and Leon, F. (2012). Multi-objective optimization of a stacked neural network using an evolutionary hyper-heuristic. *Applied Soft Computing*, 12(1), 133-144.
- Garg, B., Kirar, N., Menon, S. and Sah, T. (2016). A performance comparison of different back propagation neural networks methods for forecasting wheat production. *CSI Transactions on ICT*, 4(2), 305-311.
- Garza-Ulloa, J. (2018). Chapter 6 Application of mathematical models in biomechatronics: artificial intelligence and time-frequency analysis. In J. Garza-Ulloa (Ed.), *Applied Biomechatronics using Mathematical Models* (pp. 373-524): Academic Press.
- Ghorbani, M. A., Zadeh, H. A., Isazadeh, M. andTerzi, O. (2016). A comparative study of artificial neural network (MLP, RBF) and support vector machine models for river flow prediction. *Environmental Earth Sciences*, 75(6), 476.
- Giannakis, D. and Majda, A. J. (2015). Data-driven methods for dynamical systems:
 Quantifying predictability and extracting spatiotemporal patterns.
 Mathematical and Computational Modeling: With Applications in Natural and Social Sciences, Engineering, and the Arts, 1.
- Gibon, V. (2012). Palm oil and palm kernel oil refining and fractionation technology.In *Palm Oil* (pp. 329-375): Elsevier.
- Gibon, V., De Greyt, W. and Kellens, M. (2007). Palm oil refining. *European journal* of lipid science and technology, 109(4), 315-335.

- Goh, S. H., Choo, Y. M. and Ong, S. H. (1985). Minor constituents of palm oil. *Journal* of the American Oil Chemists' Society, 62(2), 237-240.
- Graupe, D. (2007). Principles of Artificial Neural Networks (2nd Edition) (Vol. 6).Singapore: World Scientific Publishing Co. Pte. Ltd.
- Gunawan, E. R. and Suhendra, D. (2010). Wax Esters Production by Alcoholysis of Palm Oil Fractions. 2010, 8(3), 7.
- Hajra, B., Sultana, N., Pathak, A. K. and Guria, C. (2015). Response surface method and genetic algorithm assisted optimal synthesis of biodiesel from high free fatty acid sal oil (Shorea robusta) using ion-exchange resin at high temperature. *Journal of Environmental Chemical Engineering*, 3(4, Part A), 2378-2392.
- Humbird, D. and Fei, Q. (2016). Chapter 20 Scale-Up Considerations for Biofuels.In C. A. Eckert and C. T. Trinh (Eds.), *Biotechnology for Biofuel Production* and Optimization (pp. 513-537). Amsterdam: Elsevier.
- Ibnu, C. R. M., Santoso, J. and Surendro, K. (2019). Determining the neural network topology: A review. Paper presented at the Proceedings of the 2019 8th International Conference on Software and Computer Applications.
- Işcan, B. (2020). ANN modeling for justification of thermodynamic analysis of experimental applications on combustion parameters of a diesel engine using diesel and safflower biodiesel fuels. *Fuel*, 279, 118391.
- Israyandi, Zahrina, I. and Mulia, K. (2017). Optimization process condition for deacidification of palm oil by liquid-liquid extraction using NADES (Natural Deep Eutectic Solvent). AIP Conference Proceedings, 1823(1), 020107.
- Iwuoha, C. I., Ubbaonu, C. N., Ugwo, R. C. and Okereke, N. U. (1996). Chemical and physical characteristics of palm, palm kernel and groundnut oils as affected by degumming. *Food Chemistry*, 55(1), 29-34.
- Jamali, A., Ahmadi, P. and Mohd Jaafar, M. N. (2014). Optimization of a novel carbon dioxide cogeneration system using artificial neural network and multiobjective genetic algorithm. *Applied Thermal Engineering*, 64(1), 293-306.
- James Jayaselan, H. A., Nawi, N., Wan Ismail, W. I., Mohamed Shariff, A. R., Rajah, V. and Arulandoo, X. (2017) "Application of Spectroscopy for Nutrient Prediction of Oil Palm", *Journal of Experimental Agriculture International*, 15(3), pp. 1-9.

- Japir, A. A.-W., Salimon, J., Derawi, D., Bahadi, M., Al-Shuja'a, S. and Yusop, M. R. (2017). Physicochemical characteristics of high free fatty acid crude palm oil. *OCL*, 24(5), D506.
- Jaswir, I. and Che Man, Y. B. (1999). Use optimization of natural antioxidants in refined, bleached, and deodorized palm olein during repeated deep-fat frying using response surface methodology. *Journal of the American Oil Chemists' Society*, 76(3), 341-348.
- Jin, J., Li, M. and Jin, L. (2015). Data Normalization to Accelerate Training for Linear Neural Net to Predict Tropical Cyclone Tracks. *Mathematical Problems in Engineering*, 2015, 931629.
- Kolakoti, A., Jha, P., Mosa, P. R., Mahapatro, M., and Kotaru, T. G. (2020). Optimization and modelling of mahua oil biodiesel using RSM and genetic algorithm techniques. *Mathematical Models in Engineering*, 6(2), pp.134–146.
- Kasivisvanathan, H., Ng, R. T. L., Tay, D. and Ng, D. K. S. (2012). Fuzzy optimisation for retrofitting a palm oil mill into a sustainable palm oil-based integrated biorefinery. *Chemical Engineering Journal*, 200–202, 694-709.
- Kaynak, G., Ersoz, M. and Kara, H. (2004). Investigation of the properties of oil at the bleaching unit of an oil refinery. *Journal of Colloid and Interface Science*, 280(1), 131-138.
- Khellaf, A., Yallese, M., Boutabba, S., Habak, M., Aouici, H. and Smaiah, S. (2017).
 Mathematical Modeling and Multi-Objective Optimization of Technological
 Parameters in Hard Turning Operation Using RSM and Genetic Algorithmic
 Approach.
- Khuri, A. I. (2006). Response surface methodology and related topics: World scientific.
- Khuri, A. I. and Conlon, M. (1981). Simultaneous Optimization of Multiple Responses Represented by Polynomial Regression Functions. *Technometrics*, 23(4), 363-375.
- Kim, P. (2017). *MATLAB Deep Learning: With Machine Learning, Neural Networks* and Artificial Intelligence: Apress.
- Koohestanian, E., Samimi, A., Mohebbi-Kalhori, D. and Sadeghi, J. (2017). Sensitivity analysis and multi-objective optimization of CO2CPU process using response surface methodology. *Energy*, 122, 570-578.

- Leon, F., Piuleac, C. G. and Curteanu, S. (2010). Stacked Neural Network Modeling Applied to the Synthesis of Polyacrylamide-Based Multicomponent Hydrogels. *Macromolecular Reaction Engineering*, 4(9-10), 591-598.
- Lin, S. W. and Yoo, C. K. (2007). Optimization of degumming with attapulgite and acid-activated clays in refining palm oil. *Journal of oil palm research*, *19*, 373.
- Liu, F. and Yang, M. (2005). Verification and Validation of Artificial Neural Network Models. Paper presented at the AI 2005: Advances in Artificial Intelligence, Berlin, Heidelberg.
- Luyue, X. and Haitian, P. (2010, 24-26 Aug. 2010). Inferential estimation of polypropylene melt index using stacked neural networks based on absolute error criteria. Paper presented at the 2010 International Conference on Computer, Mechatronics, Control and Electronic Engineering.
- Mahrach, M., Miranda, G., León, C. and Segredo, E. (2020). Comparison between Single and Multi-Objective Evolutionary Algorithms to Solve the Knapsack Problem and the Travelling Salesman Problem. *Mathematics*, 8(11), 2018.
- Mahu, E., Ignat, M., Cojocaru, C., Samoila, P., Coromelci, C., Asaftei, I. and Harabagiu, V. (2020). Development of Porous Titania Structure with Improved Photocatalytic Activity: Response Surface Modeling and Multi-Objective Optimization. *Nanomaterials*, 10(5), 998.
- Manan, Z. A., Siang, L. C. and Mustapa, A. N. (2009). Development of a New Process for Palm Oil Refining Based on Supercritical Fluid Extraction Technology. *Industrial & Engineering Chemistry Research*, 48(11), 5420-5426.
- Melnik, R. (2015). Universality of Mathematical Models in Understanding Nature, Society, and Man-Made World. *Mathematical and Computational Modeling*, 1-16.
- Miikkulainen, R. (2010). Topology of a Neural Network. In C. Sammut and G. I. Webb (Eds.), *Encyclopedia of Machine Learning* (pp. 988-989). Boston, MA: Springer US.
- Miriyala, S. S. and Mitra, K. (2020). Multi-objective optimization of iron ore induration process using optimal neural networks. *Materials and Manufacturing Processes*, 35(5), 537-544.

- Morad, N. A., Mohd Zin, R., Mohd Yusof, K. and Abdul Aziz, M. K. (2010). Process Modelling of Combined Degumming and Bleaching in Palm Oil Refining Using Artificial Neural Network. *Journal of the American Oil Chemists' Society*, 87(11), 1381-1388.
- Morgan, D. A., Shaw, D. B., Sidebottom, M. J., Soon, T. C. and Taylor, R. S. (1985). The function of bleaching earths in the processing of palm, palm kernel and coconut oils. *Journal of the American Oil Chemists' Society*, 62(2), 292-299.
- Mrzygłód, B., Hawryluk, M., Janik, M. and Olejarczyk-Wożeńska, I. (2020). Sensitivity analysis of the artificial neural networks in a system for durability prediction of forging tools to forgings made of C45 steel. *The International Journal of Advanced Manufacturing Technology*, 109(5), 1385-1395.
- Muhsin, W. and Zhang, J. (2017). Modelling and Optimal Operation of a Crude Oil Hydrotreating Process with Atmospheric Distillation Unit Utilising Stacked Neural Networks. In A. Espuña, M. Graells and L. Puigjaner (Eds.), *Computer Aided Chemical Engineering* (Vol. 40, pp. 2479-2484): Elsevier.
- Murata, T. and Ishibuchi, H. (1995). *MOGA: multi-objective genetic algorithms*. Paper presented at the IEEE international conference on evolutionary computation.
- Mustakim, M., Buono, A. and Hermadi, I. (2016). Performance comparison between support vector regression and artificial neural network for prediction of oil palm production. *Jurnal Ilmu Komputer dan Informasi*, *9*(1), 1-8.
- Myers, R. H., Montgomery, D. C. and Anderson-Cook, C. M. (2016). *Response* surface methodology: process and product optimization using designed experiments: John Wiley & Sons.
- Nabavi-Pelesaraei, A., Shaker-Koohi, S. and Dehpour, M. B. (2013). Modeling and optimization of energy inputs and greenhouse gas emissions for eggplant production using artificial neural network and multi-objective genetic algorithm. *International Journal of Advanced Biological and Biomedical Research*, *1*(11), 1478-1489.
- Noshad, M., Mohebbi, M., Shahidi, F. and Ali Mortazavi, S. (2012). Multi-Objective Optimization of Osmotic–Ultrasonic Pretreatments and Hot-Air Drying of Quince Using Response Surface Methodology. *Food and Bioprocess Technology*, 5(6), 2098-2110. doi:10.1007/s11947-011-0577-8

- *Oilseeds: World Markets and Trade*, United State Department of Agricultural-Foreign Agricultural Service, 2020, Production, Supply and Distribution (PS&D) database, <www.fas.usda.gov> accessed 30 January 2021.
- Olanrewaju, O., Jimoh, A.-G. and Kholopane, P. (2012). Comparing performance of MLP and RBF neural network models for predicting South Africa's energy consumption. *Journal of Energy in Southern Africa*, 23, 40-46.
- Palm oil imports latest casualty as China tightens credit. (2014, 8 May 2014). *TheStar*. Retrieved June 19, 2014, from <u>Palm oil imports latest casualty as</u> <u>China tightens credit | The Star</u>
- Pandian, P. S., Selvan, S. S., Subathira, A. and Saravanan, S. (2020). Optimization of Aqueous Two Phase Extraction of Proteins from Litopenaeus Vannamei Waste by Response Surface Methodology Coupled Multi-Objective Genetic Algorithm. *Chemical Product and Process Modeling*, 15(1).
- Pogaku, R., Anisuzzaman, S. M. and Veera Rao, V. P. R. (2015). Modeling of Free Fatty Acid Content in the Deodorization Process of Palm Oil Refinery Using Six Sigma with Response Surface Methodology. In P. Ravindra (Ed.), Advances in Bioprocess Technology (pp. 79-95). Cham: Springer International Publishing.
- Ooi, Y.-S., Zakaria, R., Mohamed, A. R. and Bhatia, S. (2004). Catalytic Cracking of Used Palm Oil and Palm Oil Fatty Acids Mixture for the Production of Liquid Fuel: Kinetic Modeling. *Energy & Fuels*, 18(5), 1555-1561.
- Prasada Rao, K., Victor Babu, T., Anuradha, G. and Appa Rao, B. V. (2017). IDI diesel engine performance and exhaust emission analysis using biodiesel with an artificial neural network (ANN). *Egyptian Journal of Petroleum*, 26(3), 593-600.
- Rashid, N. A., Mohd Rosely, N. A., Mohd. Noor, M. A., Shamsuddin, A., Abd. Hamid,
 M. K. and Asri Ibrahim, K. (2017). Forecasting of Refined Palm Oil Quality
 using Principal Component Regression. *Energy Procedia*, 142, 2977-2982.
- Rezaee, M., Basri, M., Rahman, R. N. Z. R. A., Salleh, A. B., Chaibakhsh, N. and Karjiban, R. A. (2014). Formulation development and optimization of palm kernel oil esters-based nanoemulsions containing sodium diclofenac. *International journal of nanomedicine*, 9, 539.

- Rossi, M., Gianazza, M., Alamprese, C. and Stanga, F. (2003). The role of bleaching clays and synthetic silica in palm oil physical refining. *Food Chemistry*, 82(2), 291-296.
- Sambanthamurthi, R., Sundram, K. and Tan, Y. (2000). Chemistry and biochemistry of palm oil. *Progress in lipid research*, *39*, 507-558.
- Sampaio, K. A., Ayala, J. V., Van Hoed, V., Monteiro, S., Ceriani, R., Verhé, R. and Meirelles, A. J. (2017). Impact of crude oil quality on the refining conditions and composition of nutraceuticals in refined palm oil. *Journal of food science*, 82(8), 1842-1850.
- Saneei, M., Hossein Goli, S. A. and Keramat, J. (2015). Optimization of oil bleaching parameters, using response surface methodology, for acid-activated sepiolite from Iran. *Clay Minerals*, 50(5), 639-648.
- Sedaghat Boroujeni, L., Ghavami, M., Piravi Vanak, Z. and Ghasemi Pirbalouti, A. (2020). Optimization of sunflower oil bleaching parameters: using Response Surface Methodology (RSM). *Food Science and Technology*, 40, 322-330.
- Shahbaz, M., Taqvi, S. A., Minh Loy, A. C., Inayat, A., Uddin, F., Bokhari, A. and Naqvi, S. R. (2019). Artificial neural network approach for the steam gasification of palm oil waste using bottom ash and CaO. *Renewable Energy*, 132, 243-254.
- Shanmuganathan, S. and Samarasinghe, S. (Eds.). (2016). Artificial Neural Network Modelling. Studies in Computational Intelligence. doi:10.1007/978-3-319-28495-8
- Sharifi, A. and Mohebbi, A. (2012). Introducing a new formula based on an artificial neural network for prediction of droplet size in venturi scrubbers. *Brazilian Journal of Chemical Engineering*, 29, 549-558.
- Shojaeefard, M. H., Akbari, M., Tahani, M. and Farhani, F. (2013). Sensitivity Analysis of the Artificial Neural Network Outputs in Friction Stir Lap Joining of Aluminum to Brass. Advances in Materials Science and Engineering, 2013, 574914.
- Shukri, M. R., Rahman, M., Ramasamy, D. and Kadirgama, K. (2015). Artificial Neural Network Optimization Modeling of Engine Performance of Diesel Engine Using Biodeisel Fuel. *International Journal of Automotive & Mechanical Engineering*, 11.

- Silva, C. M. and Biscaia, E. C. (2003). Genetic algorithm development for multiobjective optimization of batch free-radical polymerization reactors. *Computers & Chemical Engineering*, 27(8), 1329-1344.
- Silva, S. M., Sampaio, K. A., Ceriani, R., Verhé, R., Stevens, C., De Greyt, W. and Meirelles, A. J. A. (2014). Effect of type of bleaching earth on the final color of refined palm oil. *LWT - Food Science and Technology*, 59(2, Part 2), 1258-1264.
- Sim, B. I., Khor, Y. P., Lai, O. M., Yeoh, C. B., Wang, Y., Liu, Y., . . . Tan, C. P. (2020). Mitigation of 3-MCPD esters and glycidyl esters during the physical refining process of palm oil by micro and macro laboratory scale refining. *Food Chemistry*, 328, 127147.
- Sime Darby Oils Pasir Gudang Refinery Sdn. Bhd. (2011c). *Product Quality Specification*. Unpublished note, Sime Darby Kempas Sdn. Bhd.
- Singh, P. and Dwivedi, P. (2019). A novel hybrid model based on neural network and multi-objective optimization for effective load forecast. *Energy*, *182*, 606-622.
- Sola, J. and Sevilla, J. (1997). Importance of input data normalization for the application of neural networks to complex industrial problems. *IEEE Transactions on nuclear science*, *44*(3), 1464-1468.
- Soleimani, R., Shoushtari, N. A., Mirza, B. and Salahi, A. (2013). Experimental investigation, modeling and optimization of membrane separation using artificial neural network and multi-objective optimization using genetic algorithm. *Chemical Engineering Research and Design*, *91*(5), 883-903.
- Sridhar, D. V., Seagrave, R. C. and Bartlett, E. B. (1996). Process modeling using stacked neural networks. AIChE Journal, 42(9), 2529-2539.
- Sui Kim, I. T., Sethu, V., Arumugasamy, S. K. and Selvarajoo, A. (2020). Fenugreek seeds and okra for the treatment of palm oil mill effluent (POME) – Characterization studies and modeling with backpropagation feedforward neural network (BFNN). *Journal of Water Process Engineering*, 37, 101500.
- Sun, X. and Yoon, J. Y. (2018). Multi-objective optimization of a gas cyclone separator using genetic algorithm and computational fluid dynamics. *Powder Technology*, 325, 347-360.
- Suzuki, K. (2011). Artificial neural networks: methodological advances and biomedical applications: BoD–Books on Demand.

- Tan, C.-P. and Nehdi, I. A. (2012). 13 The Physicochemical Properties of Palm Oil and Its Components. In O.-M. Lai, C.-P. Tan and C. C. Akoh (Eds.), *Palm Oil* (pp. 377-391): AOCS Press.
- Taylor, B. J. and Skias, S. (2006). *Methods and Procedures for the Verification and Validation of Artificial Neural Networks*: Springer.
- Tehlah, N., Kaewpradit, P. and Mujtaba, I. M. (2016). Artificial neural network based modeling and optimization of refined palm oil process. *Neurocomputing*, 216, 489-501.
- Tryana Sembiring, M., Sejati Hutapea, S., Zaky Hadi, M. and Wahyuni, D. (2020). A design of bi-objective optimization model palm refinery export supply chain network: a case study in Indonesia. *IOP Conference Series: Materials Science and Engineering*, 801, 012112.
- Uslu, S. (2020). Optimization of diesel engine operating parameters fueled with palm oil-diesel blend: Comparative evaluation between response surface methodology (RSM) and artificial neural network (ANN). *Fuel*, 276, 117990.
- Usman, M. A., Ekwueme, V. I., Alaje, T. O. and Mohammed, A. O. (2012). Characterization, Acid Activation, and Bleaching Performance of Ibeshe Clay, Lagos, Nigeria. *ISRN Ceramics*, 2012, 658508.
- Usuki, R., Suzuki, T., Endo, Y. and Kaneda, T. (1984). Residual amounts of chlorophylls and pheophytins in refined edible oils. *Journal of the American Oil Chemists' Society*, *61*(4), 785-788.
- Upreti, S. R. (2017). *Process modeling and simulation for chemical engineers : theory and practice*: 7 John Wiley & Sons Ltd.
- Vijayan, D. and Abhishek, P. (2018). *Multi objective process parameters optimization of friction stir welding using NSGA–II*. Paper presented at the IOP Conference Series: Materials Science and Engineering.
- Wang, S., Xiao, J., Wang, J., Jian, G., Wen, J. and Zhang, Z. (2018). Application of response surface method and multi-objective genetic algorithm to configuration optimization of Shell-and-tube heat exchanger with fold helical baffles. *Applied Thermal Engineering*, 129, 512-520.
- Wei, P. C., May, C. Y., Ngan, M. A. and Hock, C. C. (2004). Degumming and bleaching: effect on selected constituents of palm oil. *Journal of oil palm research*, 16(2), 57-63.

- Winiczenko, R., Górnicki, K., Kaleta, A., Janaszek-Mańkowska, M., Choińska, A. and Trajer, J. (2018). Apple cubes drying and rehydration. Multiobjective optimization of the processes. *Sustainability*, 10(11), 4126.
- Yan, Z., He, A., Hara, S. and Shikazono, N. (2019). Modeling of solid oxide fuel cell (SOFC) electrodes from fabrication to operation: Microstructure optimization via artificial neural networks and multi-objective genetic algorithms. *Energy Conversion and Management, 198*, 111916.
- Yang, B., Zhou, R., Yang, J.-G., Wang, Y.-H. and Wang, W.-F. (2008). Insight into the Enzymatic Degumming Process of Soybean Oil. *Journal of the American Oil Chemists' Society*, 85(5), 421-425.
- Zhang, J. (2008). Batch-to-Batch Optimal Control of a Batch Polymerisation Process Based on Stacked Neural Network Models. *Chemical Engineering Science*, 63, 1273-1281.
- Zhou, B., Wang, T., Li, C., Fu, J., Zhang, Z., Song, Z. and Ma, C. (2020). Multiobjective optimization of the preparation parameters of the powdered activated coke for SO2 adsorption using response surface methodology. *Journal of Analytical and Applied Pyrolysis*, 146, 104776.
- Zinatizadeh, A. A. L., Mohamed, A. R., Abdullah, A. Z., Mashitah, M. D., Hasnain Isa, M. and Najafpour, G. D. (2006). Process modeling and analysis of palm oil mill effluent treatment in an up-flow anaerobic sludge fixed film bioreactor using response surface methodology (RSM). *Water Research*, 40(17), 3193-3208.
- Zulkurnain, M., Lai, O. M., Latip, R. A., Nehdi, I. A., Ling, T. C. and Tan, C. P. (2012). The effects of physical refining on the formation of 3-monochloropropane-1,2diol esters in relation to palm oil minor components. *Food Chemistry*, 135(2), 799-805.
- Zulkurnain, M., Lai, O. M., Tan, S. C., Abdul Latip, R. and Tan, C. P. (2013). Optimization of palm oil physical refining process for reduction of 3monochloropropane-1,2-diol (3-MCPD) ester formation. *J Agric Food Chem*, *61*(13), 3341-3349.

LIST OF PUBLICATIONS

Journal with Impact Factor

- Sulaiman, N. S., Mohd-Yusof, K. and Mohd-Saion, A. (2018). Quality Prediction Modeling of Palm Oil Refining Plant in Malaysia Using Artificial Neural Network Models. *International Journal of Engineering & Technology*, 7(3.26), 19-22. (2016 -2019, Q4, IF:0.11)
- Sulaiman, N. S. and Yusof, K. M. (2017). Development of optimisation model based on genetic algorithms for palm oil refining industry. *Chemical Engineering Transactions*, 56, 745-750. (Q3, IF:0.32)

Indexed Conference Proceeding

 Sulaiman, N. S. and Yusof, K. M. (2015). Artificial neural network-based model for quality estimation of refined palm oil. In 2015 15th International Conference on Control, Automation and Systems (ICCAS) (pp. 1324-1328). IEEE. (Indexed by SCOPUS)