



**UNIVERSITI PUTRA MALAYSIA**

**PREDICTING CROP YIELD AND FIELD ENERGY OUTPUT FOR OIL  
PALM USING GENETIC ALGORITHM AND NEURAL NETWORK  
MODELS**

**YOUSIF YAKOUB HILAL ALHILAL**

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By

**YOUSIF YAKOUB HILAL ALHILAL**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in  
Fulfillment of the Requirements for the Degree of Doctor of Philosophy**

**January 2019**

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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

## **PREDICTING CROP YIELD AND FIELD ENERGY OUTPUT FOR OIL PALM USING GENETIC ALGORITHM AND NEURAL NETWORK MODELS**

By

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For many years, the Malaysian oil palm industry has been facing the challenge of reduced rate of palm oil yield due to sizeable difference between the crop's actual yield and the crop's genetic yield potential. This gap has grown wider over time and has been of great concern since oil palm is a very important commodity that contributes significantly to the country's GDP. Currently, Malaysia has devoted a high percentage of the land resource and material inputs to agriculture, whereby a large proportion of them are used for oil palm cultivation. However, the typical yields are only 50–60% of the potential, and artificial intelligence research on modelling of the crop yield and energy consumption is still at its infancy.

Forecasting oil palm production and selecting significant variables that effects production are complex activities. Accurate prediction results are required for this type of analysis and can provide the basis for the decisions and plans for the management of agricultural crops in the local, regional, and global scale. In the field of agricultural engineering, artificial intelligence has helped to reduced operational periods and costs. There was not enough information available on the implementation of neural networks and genetic algorithm for the prediction and selecting input variables in oil palm yield and output energy.

This research presents the development of a GA and SW as a variables selection method in ANN and NARX models for predicting oil palm yield and output energy. Data were collected from 11 districts in 11 states in Malaysia for FFB and PO models, which includes Kedah, Kelantan, Johor, Melaka, Penang, Pahang, Perak, Selangor, Terengganu, Sabah, and Sarawak. The study is based on monthly data from 2005 to 2015. In FFB and PO models, the data used 15 variables, namely: percentage of mature area and percentage of immature area, rainfall, rainy days, humidity, radiation,

temperature, surface wind speed, evaporation and cloud cover, O<sub>3</sub>, CO, NO<sub>2</sub>, SO<sub>2</sub>, and PM<sub>10</sub>. The study used input energy data from 8 variables for developing energy models. These data included human power, electricity, fuel, water, fertilizers, and seed. Data were collected from Peninsular Malaysia, Sabah and Sarawak over a period of 11 years (annual data from 2005 to 2015).

Results showed that GA was able to select the variables correctly, while also being an easy-to-use variable selection tool. It proved to be more effective than the Stepwise. The findings of this research, using 11 years of climate change and air pollution, have significantly affected the oil palm production. Surface wind speed and humidity were recorded at an impact ratio of up to 100%, which correlated negatively on the productivity of oil palm plantations. Surface wind speed and humidity reduced the productivity of oil palm FFB plantations for 5.12 and 4.61 ton/ha/11year in the Sabah and Sarawak respectively. Additionally, the surface wind speed is considered the most essential variable recorded with an impact ratio of up to 100% on FFB in Selangor, Terengganu, and Kelantan while the cloud cover, average NO<sub>2</sub> in the air, average PM<sub>10</sub> in the air, humidity, radiation, and O<sub>3</sub> recorded the most significant impact up to 100% on FFB in Perak, Melaka, Johor, Kedah, Penang, and Pahang respectively.

Fuel consumption, water, and P-fertilizer consumption are considered the most important variables in oil palm plantation operations, its importance being the relative values of 45%, 34.3 %, and 23 %. These variables impacted oil palm operation during the 11 years at 67.764, 45.38, 16.24 GJ /ha for Peninsular Malaysia, Sabah and Sarawak, respectively. In this study, the performances of six models (namely, ANN, GA-ANN, SW- ANN, NARX, GA-NARX and SW-NARX) are compared with one another as well as with multiple linear models. The GA-NARX was chosen as the best yield model in 9 states (Perak, Sabah, Sarawak, Selangor, Terengganu, Pahang, Kedah, Kelantan and Penang), while the GA-ANN was considered the best yield model recorded in Melaka and Johor. Additionally the GA-NARX was chosen as the best energy model in Peninsular Malaysia, Sarawak and Sabah, with the average accuracy percentage simulation being 0.95.07, 95.55 and 87.43 % respectively.

Finally, this research concluded that a genetic algorithm is useful for selecting input variables in oil palm production. It is a user-friendly variable selection tool with excellent results compared to Stepwise, especially in a large search space. The GA-ANN and GA-NARX models perform markedly better than the other models in the most training algorithms with different numbers of hidden layers.

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

**MERAMALKAN HASIL TANAMAN DAN TENAGA OUTPUT LAPANGAN  
UNTUK MINYAK KELAPA SAWIT MENGGUNAKAN ALGORITMA  
GENETIK DAN MODEL RANGKAIAN NEURAL**

Oleh

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Selama beberapa tahun industri kelapa sawit Malaysia menghadapi cabaran penurunan kadar hasil kelapa sawit disebabkan oleh perbezaan ketara antara hasil sebenar tanaman dengan kemampuan hasil genetik tanaman. Perbezaan ini telah membesar dengan masa dan telah menjadi satu kebimbangan disebabkan kelapa sawit merupakan komoditi yang terpenting yang menyumbang secara signifikan kepada KDNK negara. Buat masa ini, Malaysia telah memperuntukkan peratusan yang tinggi dalam sumber tanah dan input bahan untuk pertanian dimana kadaran yang tersangat besar digunakan untuk penanaman kelapa sawit. Walau bagaimanapun, hasil lazimnya kelapa adalah hanya 50–60% daripada hasil potensinya manakala penyelidikan kecerdasan buatan dalam pemodelan hasil tanaman dan penggunaan tenaga adalah masih pada peringkat awal.

Peramalan pengeluaran kelapa sawit dan pemilihan pemboleh ubah yang signifikan dalam memberi kesan pada pengeluaran adalah aktiviti yang kompleks. Dapatan ramalan yang tepat diperlukan untuk analisis dan yang dapat memberikan asas bagi keputusan dan perancangan bagi pengurusan tanaman pertanian pada skala tempatan, regional, dan global. Dalam bidang kejuruteraan pertanian, kemajuan dalam kecerdasan buatan telah dapat membantu dalam mengurangkan julat masa kendalian dan kos. Tiada terdapat pengetahuan yang mendalam mengenai penggunaan rangkaian neural dan algoritma genetik dalam ramalan dan pemilihan pemboleh ubah input bagi hasil kelapa sawit dan keluaran tenaga.

Penyelidikan ini membentangkan pembangunan GA dan SW sebagai kaedah pemilihan pembolehubah dalam ANN dan NARX model untuk meramalkan hasil kelapa sawit dan keluaran tenaga. Data dikumpulkan dari 11 daerah di 11 negeri di Malaysia bagi model FFB dan PO, termasuk Kedah, Kelantan, Johor, Melaka, Pulau Pinang, Pahang, Perak,

Selangor, Terengganu, Sabah dan Sarawak. Kajian ini berdasarkan pada data bulanan dari tahun 2005 hingga 2015. Dalam model FFB dan PO, data telah menggunakan 15 pembolehubah, iaitu: peratusan kawasan matang dan peratusan kawasan yang tidak matang, hujan, hari hujan, kelembapan, radiasi, suhu, kelajuan permukaan angin, penyejatan dan penutup awan, O<sub>3</sub>, CO, NO<sub>2</sub>, SO<sub>2</sub>, and PM<sub>10</sub>. Kajian ini menggunakan input data tenaga dari 8 pembolehubah untuk membangunkan model tenaga. Data ini termasuk kuasa manusia, elektrik, bahan api, air, baja dan biji. Data dikumpulkan dari Semenanjung Malaysia, Sabah dan Sarawak sepanjang tempoh 11 tahun (data tahunan 2005 hingga 2015).

Keputusan menunjukkan bahawa GA dapat memilih pembolehubah dengan betul, sementara ia juga merupakan alat pemilihan pembolehubah yang mudah digunakan. Ia terbukti lebih efektif daripada Stepwise. Dapatan kajian ini yang menggunakan 11 tahun perubahan cuaca dan pencemaran udara yang mempengaruhi pengeluaran kelapa sawit telah dilaporkan adalah signifikan. Kelajuan dan kelembapan permukaan angin direkodkan pada kesan nisbah sehingga 100%, yang berkorelasi negatif terhadap produktiviti ladang kelapa sawit. Kelajuan dan kelembapan permukaan angin telah mengurangkan produktiviti ladang FFB kelapa sawit masing-masing 5.12 dan 4.61 ton/ha/11 tahun di Sabah dan Sarawak. Tambahan pula, kelajuan permukaan angin dianggap sebagai pembolehubah yang paling penting yang direkodkan dengan kesan nisbah sehingga 100% pada FFB di Selangor, Terengganu, dan Kelantan manakala penutup awan, purata NO<sub>2</sub> di udara, purata PM<sub>10</sub> di udara, kelembapan, radiasi, dan O<sub>3</sub> mencatat kesan yang paling signifikan sehingga 100% pada FFB masing-masing di Perak, Melaka, Johor, Kedah, Pulau Pinang dan Pahang.

Penggunaan bahan api, air, dan penggunaan P-baja dianggap pembolehubah yang paling penting dalam operasi ladang kelapa sawit, kepentingannya adalah nilai relatif 45%, 34.3%, dan 23%. Pembolehubah ini telah mempengaruhi operasi kelapa sawit selama 11 tahun di 67.764, 45.38, 16.24 GJ / ha masing-masing di Semenanjung Malaysia, Sabah dan Sarawak. Dalam kajian ini, prestasi enam model (iaitu, ANN, GA-ANN, SW-ANN, NARX, GA-NARX dan SW-NARX) dapat dibandingkan antara satu sama lain dan dengan model berganda. GA-NARX dipilih sebagai model hasil terbaik di 9 buah negeri (Perak, Sabah, Sarawak, Selangor, Terengganu, Pahang, Kedah, Kelantan dan Pulau Pinang) manakala GA-ANN dianggap model hasil terbaik yang direkodkan di Melaka dan Johor. Selain itu, GA-NARX telah dipilih sebagai model tenaga terbaik di Semenanjung Malaysia, Sarawak dan Sabah dengan purata peratusan ketepatan simulasi masing-masing iaitu 0.95.07, 95.55 dan 87.43%.

Akhirnya, kajian ini telah menyimpulkan bahawa algoritma genetik adalah berguna untuk memilih pembolehubah input dalam pengeluaran kelapa sawit. Ia adalah pilihan alat pembolehubah yang mesra pengguna dengan keputusan yang cemerlang berbanding dengan Stepwise terutamanya dalam ruang carian yang besar. Model GA-ANN dan GA-NARX adalah ketara lebih baik daripada model lain dalam kebanyakan algoritma latihan dengan bilangan lapisan tersembunyi yang berbeza.

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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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## TABLE OF CONTENTS

		<b>Page</b>
<b>ABSTRACT</b>		i
<b>ABSTRAK</b>		iii
<b>ACKNOWLEDGEMENTS</b>		v
<b>APPROVAL</b>		vi
<b>DECLARATION</b>		viii
<b>LIST OF TABLES</b>		xiv
<b>LIST OF FIGURES</b>		xxii
<b>LIST OF ABBREVIATIONS</b>		xxix
<b>CHAPTER</b>		
<b>1</b>	<b>INTRODUCTION</b>	1
	1.1 Background	1
	1.2 Oil Palm Yield and Energy	2
	1.3 Genetic Algorithm and Neural Network Hybrid	3
	1.4 Problem Statement	5
	1.5 Research Objectives	6
	1.6 Scope of the Study	7
	1.7 Thesis Layout	8
<b>2</b>	<b>LITERATURE REVIEW</b>	9
	2.1 Introduction	9
	2.2 Oil Palm	9
	2.2.1 Global Importance of Oil Palm	10
	2.2.2 Oil Palm Production in Malaysia	14
	2.3 Maturity Stages and Environmental Factors	17
	2.3.1 Maturity Stages	17
	2.3.2 Climate Change and Oil Palm	18
	2.3.3 Air Pollution Relation and Oil Palm	20
	2.3.4 Interaction Effects between Climate Change, Air Pollution and Oil Palm.	22
	2.4 Energy	23
	2.4.1 Concept of Energy	23
	2.4.2 Energy Sources in Malaysia Oil Palm	24
	2.4.2.1 Human Power	24
	2.4.2.2 Diesel Fuel	25
	2.4.2.3 Fertilizer	25
	2.4.2.4 Water for Irrigation	26
	2.4.2.5 Electricity	27
	2.4.2.6 Seed	27
	2.5 Input Variable Selection Methods	28
	2.5.1 Importance of Input Variable Selection	29
	2.5.2 Taxonomy of Input Variable Selection	29
	2.6 Stepwise Selection (SW)	31
	2.7 Genetic Algorithm (GA)	32

	2.7.1	Structure and Operation of a Basic Genetic Algorithm	33
	2.7.2	Genetic Algorithm Applications	33
2.8		Neural Networks	34
	2.8.1	The Neuron and Transfer Function	35
	2.8.2	Network Architecture and Number of Layers	36
	2.8.3	Learning Rules and Training Function	37
	2.8.4	Neural Network Types	38
	2.8.5	Classical Artificial Neural Networks.	38
	2.8.6	Time-Series NARX Neural Networks	39
	2.8.7	Applications of ANN and NARX	41
2.9		Modelling	42
	2.9.1	Oil Palm Yield Modeling	43
	2.9.2	Oil Palm Energy Modeling	45
2.10		Summary	47
<b>3</b>		<b>MATERIALS AND METHODS</b>	<b>48</b>
	3.1	Introduction	48
	3.2	General Information about the Sites Analysis	48
	3.3	Collection of Input and Output Data	52
	3.4	Data Validation and Exploration	56
	3.5	Development of the Model Selection Based on GA for Crop Yield and Energy	57
	3.6	Development of the Model Selection Based on Stepwise for Crop Yield and Energy	62
	3.7	Development of ANN Models for Crop Yield and Energy	64
	3.8	Development of NARX Models for Crop Yield and Energy	71
	3.9	Development of Linear Models (Mathematical Models) for Crop Yield and Energy	74
	3.10	Forecasting Simulation Models	76
	3.11	Sensitivity Test for the Optimal Model	77
<b>4</b>		<b>RESULTS AND DISCUSSION</b>	<b>79</b>
	4.1	Introduction	79
	4.2	Development of Oil Palm Yield Models	79
	4.2.1	Kedah	80
		4.2.1.1 Mathematical Model	80
		4.2.1.2 Selection Variables	83
		4.2.1.3 ANN and NARX Models	87
		4.2.1.4 GA with ANN and NARX Models	89
		4.2.1.5 Stepwise with ANN and NARX Models	91
		4.2.1.6 Simulation and Selecting Model	95
		4.2.1.7 Sensitivity Analysis	96
	4.2.2	Kelantan	98
		4.2.2.1 Mathematical Model	99
		4.2.2.2 Selection Variables	101
		4.2.2.3 ANN and NARX Models	104
		4.2.2.4 GA with ANN and NARX Models	106

	4.2.2.5	Stepwise with ANN and NARX Models	108
	4.2.2.6	Simulation and Selecting Model	111
	4.2.2.7	Sensitivity Analysis	112
4.2.3	Johor		113
	4.2.3.1	Mathematical Models	114
	4.2.3.2	Selection Variables	116
	4.2.3.3	ANN and NARX Models	119
	4.2.3.4	GA with ANN and NARX Models	121
	4.2.3.5	Stepwise with ANN and NARX Models	124
	4.2.3.6	Simulation and Selecting Model	127
	4.2.3.7	Sensitivity Analysis	128
4.2.4	Melaka		130
	4.2.4.1	Mathematical Model	130
	4.2.4.2	Selection Variables	133
	4.2.4.3	ANN and NARX Models	136
	4.2.4.4	GA with ANN and NARX Models	138
	4.2.4.5	Stepwise with ANN and NARX Models	140
	4.2.4.6	Simulation and Selecting Model	143
	4.2.4.7	Sensitivity Analysis	144
4.2.5	Penang		146
	4.2.5.1	Mathematical Model	146
	4.2.5.2	Selection Variables	148
	4.2.5.3	ANN and NARX Models	150
	4.2.5.4	GA with ANN and NARX Models	152
	4.2.5.5	Stepwise with ANN and NARX Models	154
	4.2.5.6	Simulation and Selecting Model	156
	4.2.5.7	Sensitivity Analysis	158
4.2.6	Perak		159
	4.2.6.1	Mathematical Model	160
	4.2.6.2	Selection Variables	162
	4.2.6.3	ANN and NARX Models	165
	4.2.6.4	GA with ANN and NARX Models	167
	4.2.6.5	Stepwise with ANN and NARX Models	169
	4.2.6.6	Simulation and Selecting Model	171
	4.2.6.7	Sensitivity Analysis	173
4.2.7	Pahang		174
	4.2.7.1	Mathematical Model	174
	4.2.7.2	Selection Variables	177
	4.2.7.3	ANN and NARX Models	179
	4.2.7.4	GA with ANN and NARX Models	181
	4.2.7.5	Stepwise with ANN and NARX Models	183
	4.2.7.6	Simulation and Selecting Model	185
	4.2.7.7	Sensitivity Analysis	187

4.2.8	Selangor	188
4.2.8.1	Mathematical Model	189
4.2.8.2	Selection Variables	191
4.2.8.3	ANN and NARX Models	193
4.2.8.4	GA with ANN and NARX Models	195
4.2.8.5	Stepwise with ANN and NARX Models	197
4.2.8.6	Simulation and Selecting Model	198
4.2.8.7	Sensitivity Analysis	200
4.2.9	Terengganu	202
4.2.9.1	Mathematical Model	202
4.2.9.2	Selection Variables	204
4.2.9.3	ANN and NARX Models	207
4.2.9.4	GA with ANN and NARX Models	208
4.2.9.5	Stepwise with ANN and NARX Models	210
4.2.9.6	Simulation and Selecting Model	212
4.2.9.7	Sensitivity Analysis	213
4.2.10	Borneo (Sabah and Sarawak) Malaysia's	214
4.2.10.1	Mathematical Model	215
4.2.10.2	Selection Variables	219
4.2.10.3	ANN and NARX Models	223
4.2.10.4	GA with ANN and NARX Models	226
4.2.10.5	Stepwise with ANN and NARX Models	230
4.2.10.6	Simulation and Selecting Model	233
4.2.10.7	Sensitivity Analysis	235
4.3	Development of Energy Models	238
4.3.1	Mathematical Model	238
4.3.2	Selection Variables	241
4.3.3	ANN and NARX Models	244
4.3.4	GA with ANN and NARX Models	249
4.3.5	Stepwise with ANN and NARX Models	253
4.3.6	Simulation and Selecting Model	257
4.3.7	Sensitivity Analysis	260
4.4	Summary of results	263
<b>5</b>	<b>CONCLUSIONS AND RECOMMENDATIONS</b>	<b>265</b>
5.1	Conclusions	265
5.2	Recommendations	267
5.3	Research Contribution	267
	<b>REFERENCES</b>	<b>269</b>
	<b>APPENDICES</b>	<b>296</b>
	<b>BIODATA OF STUDENT</b>	<b>314</b>
	<b>LIST OF PUBLICATIONS</b>	<b>315</b>

## LIST OF TABLES

Table		Page
2.1	Wind properties in relation to suitability for oil palm growing	20
2.2	Human energy in agricultural operation	25
2.3	Equivalent water energy in oil palm plantation	26
3.1	Description of the study sites	51
3.2	Input and output data for FFB and PO models	52
3.3	Input and output data for output energy models	54
3.4	Energy coefficients of different inputs and outputs used in oil palm production	55
3.5	LM training parameters with their default values	68
3.6	RP training parameters with their default values	69
3.7	GDX training parameters with their default values	70
4.1	ANOVA for response surface linear model FFB in Kedah.	81
4.2	ANOVA for response surface linear model PO in Kedah	81
4.3	The performance of the mathematical model in Kedah	82
4.4	The model selection for Kedah	86
4.5	Performance of model selection by Stepwise in Kedah	86
4.6	The performance of the ANN models in Kedah	87
4.7	The performance of the NARX models in Kedah	88
4.8	The performance of the GA-ANN models in Kedah	90
4.9	The performance of the GA-NARX models in Kedah	90
4.10	The performance of the SW-ANN models in Kedah	93
4.11	The performance of the SW-NARX models in Kedah	93



4.12	Simulation models of FFB in Kedah	95
4.13	Simulation models of PO in Kedah	96
4.14	ANOVA for Response Surface Linear model FFB in Kelantan	99
4.15	ANOVA for Response Surface Linear model PO in Kelantan	100
4.16	The performance of the mathematical model in Kelantan	100
4.17	The model selection for Kelantan	103
4.18	Performance of model selection by Stepwise in Kelantan	103
4.19	The performance of the ANN models in Kelantan	104
4.20	The performance of the NARX models in Kelantan	105
4.21	The performance of the GA-ANN models in Kelantan	107
4.22	The performance of the GA-NARX models in Kelantan	107
4.23	The performance of the SW-ANN models in Kelantan	109
4.24	The performance of the SW-NARX models in Kelantan	110
4.25	Simulation models of FFB in Kelantan	111
4.26	Simulation models of PO in Kelantan	112
4.27	ANOVA for Response Surface Linear model FFB in Johor	114
4.28	ANOVA for Response Surface Linear model PO in Johor	115
4.29	The performance of the mathematical model in Johor	115
4.30	The model selection for Johor	119
4.31	Performance of model selection by Stepwise in Johor	119
4.32	The performance of the ANN models in Johor	120
4.33	The performance of the NARX models in Johor	120
4.34	The performance of the GA-ANN models in Johor	122
4.35	The performance of the GA-NARX models in Johor	123

4.36	The performance of the SW-ANN models in Johor	125
4.37	The performance of the SW-NARX models in Johor	125
4.38	Simulation models of FFB in Johor	127
4.39	Simulation models of PO in Johor.	128
4.40	ANOVA for Response Surface Linear model FFB in Melaka	131
4.41	ANOVA for Response Surface Linear model PO in Melaka	131
4.42	The performance of the mathematical model in Melaka	133
4.43	The model selection for Melaka	135
4.44	Performance of model selection by Stepwise in Melaka	135
4.45	The performance of the ANN models in Melaka	136
4.46	The performance of the NARX models in Melaka	137
4.47	The performance of the GA-ANN models in Melaka	138
4.48	The performance of the GA-NARX models in Melaka	139
4.49	The performance of the SW-ANN models in Melaka	141
4.50	The performance of the SW-NARX models in Melaka	142
4.51	Simulation models of FFB in Melaka	143
4.52	Simulation models of PO in Melaka	144
4.53	ANOVA for Response Surface Linear model FFB in Penang	146
4.54	ANOVA for Response Surface Linear model PO in Penang	147
4.55	The performance of the mathematical model in Penang	147
4.56	The model selection for Penang	150
4.57	Performance of model selection by Stepwise in Penang	150
4.58	The performance of the ANN models in Penang	151
4.59	The performance of the NARX models in Penang	152

4.60	The performance of the GA-ANN models in Penang	153
4.61	The performance of the GA-NARX models in Penang	154
4.62	The performance of the SW-ANN models in Penang	155
4.63	The performance of the SW-NARX models in Penang	156
4.64	Simulation models of FFB in Penang	157
4.65	Simulation models of PO in Penang	157
4.66	ANOVA for Response Surface Linear model FFB in Perak	160
4.67	ANOVA for Response Surface Linear model PO in Perak	161
4.68	The performance of the mathematical model in Perak	161
4.69	The model selection for Perak	165
4.70	Performance of model selection by Stepwise in Perak	165
4.71	The performance of the ANN models in Perak	166
4.72	The performance of the NARX models in Perak	166
4.73	The performance of the GA-ANN models in Perak	168
4.74	The performance of the GA-NARX models in Perak	168
4.75	The performance of the SW-ANN models in Perak	170
4.76	The performance of the SW-NARX models in Perak	170
4.77	Simulation models of FFB in Perak	172
4.78	Simulation models of PO in Perak	172
4.79	ANOVA for Response Surface Linear model FFB in Pahang	175
4.80	ANOVA for Response Surface Linear model PO in Pahang	175
4.81	The performance of the mathematical model in Pahang	176
4.82	The model selection for Pahang	179
4.83	Performance of model selection by Stepwise in Pahang	179

4.84	The performance of the ANN models in Pahang	180
4.85	The performance of the NARX models in Pahang	181
4.86	The performance of the GA-ANN models in Pahang	182
4.87	The performance of the GA-NARX models in Pahang	182
4.88	The performance of the SW-ANN models in Pahang	184
4.89	The performance of the SW-NARX models in Pahang	184
4.90	Simulation models of FFB in Pahang	186
4.91	Simulation models of PO in Pahang	186
4.92	ANOVA for Response Surface Linear model FFB in Selangor	189
4.93	ANOVA for Response Surface Linear model PO in Selangor	190
4.94	The performance of the mathematical model in Selangor	190
4.95	The model selection for Selangor	193
4.96	Performance of model selection by Stepwise in Selangor	193
4.97	The performance of the ANN models in Selangor	194
4.98	The performance of the NARX models in Selangor	194
4.99	The performance of the GA-ANN models in Selangor	196
4.100	The performance of the GA-NARX models in Selangor	196
4.101	The performance of the SW-ANN models in Selangor	197
4.102	The performance of the SW-NARX models in Selangor	198
4.103	Simulation models of FFB in Selangor	199
4.104	Simulation models of PO in Selangor.	200
4.105	ANOVA for Response Surface Linear model FFB in Terengganu	202
4.106	ANOVA for Response Surface Linear model PO in Terengganu	203
4.107	The performance of the mathematical model in Terengganu	203

4.108	The model selection for Terengganu	206
4.109	Performance of model selection by Stepwise in Terengganu	206
4.110	The performance of the ANN models in Terengganu	207
4.111	The performance of the NARX models in Terengganu	208
4.112	The performance of the GA-ANN models in Terengganu.	209
4.113	The performance of the GA-NARX models in Terengganu.	209
4.114	The performance of the SW-ANN models in Terengganu	211
4.115	The performance of the SW-NARX models in Terengganu	211
4.116	Simulation models of FFB in Terengganu	212
4.117	Simulation models of PO in Terengganu	213
4.118	ANOVA for Response Surface Linear model FFB in Sabah	215
4.119	ANOVA for Response Surface Linear model PO in Sabah	216
4.120	ANOVA for Response Surface Linear model FFB in Sarawak	216
4.121	ANOVA for Response Surface Linear model PO in Sarawak	217
4.122	The performance of the mathematical model in Sabah	219
4.123	The performance of the mathematical model in Sarawak	219
4.124	The model selection for Sabah and Sarawak	222
4.125	Performance of model selection by Stepwise in Sabah and Sarawak	222
4.126	The performance of the ANN models in Sabah	223
4.127	The performance of the ANN models in Sarawak.	224
4.128	The performance of the NARX models in Sabah	225
4.129	The performance of the NARX models in Sarawak.	225
4.130	The performance of the GA-ANN models in Sabah	227
4.131	The performance of the GA-ANN models in Sarawak	227

4.132	The performance of the GA-NARX models in Sabah	228
4.133	The performance of the GA-NARX models in Sarawak	228
4.134	The performance of the SW-ANN models in Sabah	231
4.135	The performance of the SW-ANN models in Sarawak	231
4.136	The performance of the SW-NARX models in Sabah	231
4.137	The performance of the SW-NARX models in Sarawak	232
4.138	Simulation models of FFB in Sabah	233
4.139	Simulation models of PO in Sabah	234
4.140	Simulation models of FFB in Sarawak	234
4.141	Simulation models of PO in Sarawak	235
4.142	ANOVA for Response Surface Linear model energy in Peninsular Malaysia	238
4.143	ANOVA for Response Surface Linear model energy in Sabah	239
4.144	ANOVA for Response Surface Linear model energy in Sarawak	239
4.145	The performance of the mathematical model	240
4.146	The model selection	244
4.147	Performance of energy model selection by Stepwise	244
4.148	The performance of the ANN models in Peninsular Malaysia	246
4.149	The performance of the ANN models in Sabah.	246
4.150	The performance of the ANN models at Sarawak	247
4.151	The performance of the NARX models	248
4.152	The performance of the GA-ANN models in Peninsular Malaysia	250
4.153	The performance of the GA-ANN models in Sabah	250
4.154	The performance of the GA-ANN models in Sarawak	251
4.155	The performance of the GA-NARX models	251

4.156	The performance of the SW-ANN models in Peninsular Malaysia	254
4.157	The performance of the SW-ANN models in Sabah	254
4.158	The performance of the SW-ANN models at Sarawak	255
4.159	The performance of the SW-NARX models	255
4.160	Final prediction models for FFB, PO and output energy	264



## LIST OF FIGURES

Figure	Page	
2.1	Global oils and fats in 2015	11
2.2	Oil palm efficiency vs. other major oil crops	12
2.3	Global palm oil production from 2005 to 2015	12
2.4	World consumption of major oils and fats in 2016	13
2.5	PO production in Malaysia and Indonesia	14
2.6	Global palm oil production in 2015	15
2.7	Distribution of the yield of FFB and PO during 41 years	16
2.8	Global price for FFB and PO during 11 years	16
2.9	The curve of yield phases	18
2.10	Fertilizer nutrient (NPK) consumption	26
2.11	Monthly demand for germination seeds 2014/2015	28
2.12	Taxonomy of IVS	30
2.13	The flowchart of the genetic algorithm	33
2.14	Neural Network Architectures	36
2.15	Main architectures of neural networks	37
2.16	Block diagram of NARX	40
2.17	Sample NARX network series-parallel architecture (open - loop) structure	41
2.18	Sample NARX network parallel network (closed - loop)	41
2.19	Analysis energy consumption in agricultural production	46
3.1	Overall methodology of the work	50
3.2	Oil palm planted area by states	51



3.3	Steps of the approach to fill the missing values	56
3.4	The flow chart of the GA-CA programmer	61
3.5	The flow chart of the Stepwise programmer	64
3.6	Input and output variables of the ANN architecture	66
3.7	Input and output variables by GA and Stepwise in the ANN architecture	67
3.8	Log and Tan - sigmoid transfer function	70
3.9	Snapshot of NARX model	71
3.10	Input and output variables of the NARX architecture	72
3.11	Input and output variables by GA and Stepwise in the NARX architecture	73
3.12	Analysis of the Variables Importance	78
4.1	The scatter plot of the predicted vs. actual for FFB model in Kedah	83
4.2	The scatter plot of the predicted vs. actual for PO model in Kedah	83
4.3	The best fitness value of genetic algorithm performance in Kedah	85
4.4	The scatter plots of ANN and NARX model predicted vs. actual values in Kedah	89
4.5	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Kedah	91
4.6	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Kedah	94
4.7	The most significant independent variables for Kedah	98
4.8	The scatter plot of the predicted vs. actual for FFB model in Kelantan	101
4.9	The scatter plot of the predicted vs. actual for PO model in Kelantan	101
4.10	The best fitness value of genetic algorithm performance in Kelantan	102
4.11	The scatter plots of ANN and NARX models predicted vs. actual values in Kelantan	106

4.12	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Kelantan	108
4.13	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Kelantan	110
4.14	The most significant independent variables for Kelantan	113
4.15	The scatter plot of the predicted vs. actual for FFB model in Johor	116
4.16	The scatter plot of the predicted vs. actual for PO model in Johor	116
4.17	The best fitness value of genetic algorithm performance in Johor	118
4.18	The scatter plots of ANN and NARX models predicted vs. actual values in Johor	121
4.19	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Johor	123
4.20	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Johor	126
4.21	The most significant independent variables for Johor	129
4.22	The scatter plot of the predicted vs. actual for FFB model in Melaka	132
4.23	The scatter plot of the predicted vs. actual for PO model in Melaka	132
4.24	The best fitness value of genetic algorithm performance in Melaka	134
4.25	The scatter plots of ANN and NARX models predicted vs. actual values in Melaka	137
4.26	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Melaka	140
4.27	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Melaka	142
4.28	The most significant independent variables for Melaka	145
4.29	The scatter plot of the predicted vs. actual for FFB model in Penang	148
4.30	The scatter plot of the predicted vs. actual for PO model in Penang	148
4.31	The best fitness value of genetic algorithm performance in Penang	149

4.32	The scatter plots of ANN and NARX models predicted vs. actual values in Penang	152
4.33	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Penang	154
4.34	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Penang	156
4.35	The most significant independent variables for Penang	159
4.36	The scatter plot of the predicted vs. actual for FFB model in Perak.	162
4.37	The scatter plot of the predicted vs. actual for PO model in Perak	162
4.38	The best fitness value of genetic algorithm performance in Perak	164
4.39	The scatter plots of ANN and NARX models predicted vs. actual values in Perak	167
4.40	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Perak	169
4.41	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Perak	171
4.42	The most significant independent variables for Perak	173
4.43	The scatter plot of the predicted vs. actual for FFB model in Pahang	176
4.44	The scatter plot of the predicted vs. actual for PO model in Pahang	177
4.45	The best fitness value of genetic algorithm performance in Pahang.	178
4.46	The scatter plots of ANN and NARX models predicted vs. actual values in Pahang	181
4.47	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Pahang	183
4.48	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Pahang	185
4.49	The most significant independent variables for Pahang	188
4.50	The scatter plot of the predicted vs. actual for FFB model in Selangor	191
4.51	The scatter plot of the predicted vs. actual for PO model in Selangor.	191

4.52	The best fitness value of genetic algorithm performance in Selangor	192
4.53	The scatter plots of ANN and NARX models predicted vs. actual values in Selangor	195
4.54	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Selangor	197
4.55	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Selangor	198
4.56	The most significant independent variables for Selangor	201
4.57	The scatter plot of the predicted vs. actual for FFB model in Terengganu	204
4.58	The scatter plot of the predicted vs. actual for PO model in Terengganu	204
4.59	The best fitness value of genetic algorithm performance in Terengganu	205
4.60	The scatter plots of ANN and NARX models predicted vs. actual values in Terengganu	208
4.61	The scatter plots of GA-ANN and GA-NARX models predicted vs. actual values in Terengganu	210
4.62	The scatter plots of SW-ANN and SW-NARX models predicted vs. actual values in Terengganu	212
4.63	The most significant independent variables for Terengganu	214
4.64	The scatter plot of the predicted vs. actual for FFB model in Sabah	217
4.65	The scatter plot of the predicted vs. actual for PO model in Sabah	218
4.66	The scatter plot of the predicted vs. actual for FFB model in Sarawak	218
4.67	The scatter plot of the predicted vs. actual for PO model in Sarawak	218
4.68	The best fitness value of genetic algorithm performance in Sabah	220
4.69	The best fitness value of genetic algorithm performance in Sarawak	221
4.70	The scatter plots of ANN and NARX models predicted vs. actual values in Sabah	225

4.71	The scatter plots of ANN and NARX models predicted <i>vs.</i> actual values in Sarawak	226
4.72	The scatter plots of GA-ANN and GA-NARX models predicted <i>vs.</i> actual values in Sabah	229
4.73	The scatter plots of GA-ANN and GA-NARX models predicted <i>vs.</i> actual values in Sarawak	230
4.74	The scatter plots of SW-ANN and SW-NARX models predicted <i>vs.</i> actual values in Sabah	232
4.75	The scatter plots of SW-ANN and SW-NARX models predicted <i>vs.</i> actual values in Sarawak	232
4.76	The most significant independent variables for Sabah	236
4.77	The most significant independent variables for Sarawak.	237
4.78	The scatter plot of the predicted <i>vs.</i> actual for energy model in Peninsular Malaysia	240
4.79	The scatter plot of the predicted <i>vs.</i> actual for energy model in Sabah.	241
4.80	The scatter plot of the predicted <i>vs.</i> actual for energy model in Sarawak	241
4.81	The best fitness value of genetic algorithm performance in Peninsular Malaysia	242
4.82	The best fitness value of genetic algorithm performance in Sabah	243
4.83	The best fitness value of genetic algorithm performance in Sarawak	243
4.84	The scatter plots of ANN models predicted <i>vs.</i> actual energy values.	247
4.85	The scatter plots of NARX models predicted <i>vs.</i> actual energy values	249
4.86	The scatter plots of GA-ANN models predicted <i>vs.</i> actual energy values	252
4.87	The scatter plots of GA-NARX models predicted <i>vs.</i> actual energy values	253
4.88	The scatter plots of SW-ANN models predicted <i>vs.</i> actual energy values	256

4.89	The scatter plots of SW-NARX models predicted vs. actual energy values	257
4.90	Simulation models of output energy in Peninsular Malaysia	258
4.91	Simulation models of output energy in Sabah	259
4.92	Simulation models of output energy in Sarawak	260
4.93	The most significant independent variables for Peninsular Malaysia	261
4.94	The most significant independent variables for Sabah	262
4.95	The most significant independent variables for Sarawak	262

## LIST OF ABBREVIATIONS

AAR	Applied Agricultural Resources
AAP	Average Accuracy percentage
Af	Worldwide zones of Tropical rainforest climate
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Air Pollutants Included
APSIM	Agricultural Production Systems Simulator
ASAE	American Society of Association Executives
AR	Autoregressive model
ARMA	Autoregressive–Moving-Average models
ARX	Autoregressive with exogenous terms model
BP	Back Propagation Algorithm
CA	Correlation Analysis
R	Correlation Coefficient
CPO	Crude Palm Oil
FFB	Fresh Fruit Bunch
GA	Genetic Algorithm
GHG	Greenhouse Gas
GDX	Gradient Descent with momentum and adaptive learning rate algorithm
GUI	Graphical User Interface
H	Number of neurons at hidden layers
IFA	International Fertilizer Association

IVI	Independent Variable Importance
IVS	input variable selection
LM	Levenberg-Marquardt backpropagation algorithm
MSE	Mean Squared Error
MPOB	Malaysian Palm Oil Board
MAPE	Mean Absolute Percentage Error
NARX	Nonlinear Autoregressive Exogenous Neural Network
NN	Neural Network
OPSIM	Operations Simulator
PO	Palm Oil
RP	Resilient backpropagation algorithm
SW	Stepwise
TDL	Tapped Delay Line
Te.	Testing Phase
Tr.	Training Phase
USDA	United States Department of Agriculture
Val.	Validation Phase



# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Oil palm is one of the most significant agricultural products in southeast Asia, Africa and South America. The oil palm tree (*Elaeis guineensis jacq*) is a monocotyledonous perennial plant indigenous to West Africa. The consumption of its product, palm oil, goes back as far as 5000 years to ancient Egypt. Oil palms are widely grown in more than 43 countries located mainly between 10° N and 10° S of the equator (Corley & Tinker, 2016). Today, products of oil palm feed are consumed in excess by three billion people in more than 150 countries worldwide. It is interesting to note that palm oil and its many derivative products are available in more than 40% of the packaged products in the world, and palm kernel meal is popularly used as fertilizer and livestock feed. Lately, there has been a growing demand for renewable energy; consequently, palm oil is widely used in the production of biodiesel (Fairhurst & Griffiths, 2014).

Oil palm allocations in Indonesia (10 million hectares), Malaysia (5 million hectares) and Nigeria (3 million hectares) comprise approximately 10% of the world's permanent cropland. Malaysia and Indonesia have been the hubs of this vibrant development, with both countries increasing oil palm land usage by 40% and 150%, respectively, over the last 10 years. Together, they now supply more than 80% of the world's palm oil production (FAO, 2016).

The local demand for vegetable oils is predicted to grow by 36% within the next 10 years, with biofuels making up one-third of the increase. As worldwide requirements continue to increase, available land decreases in the traditional production centres (USDA, 2015). The worldwide need for palm oil for consumption purposes is predicted to continue to increase as a result of world population growth, higher per capita consumption, and the developed world's significant shift away from unhealthy animal fats to healthy vegetable oils. In the 2014 to 2015 period, for both the EU and the US, per capita consumption of oils and fats was 60.5 kg and 59 kg, respectively. This represents a large number of consumption in comparison to developing countries such as India, Pakistan, and Nigeria, which possesses per capita consumption for oil and fats of 16.3 kg, 21.7 kg and 14 kg, respectively. With increasing income levels in the developing world, there will be a need for greater production levels of vegetable oil to satisfy the increased demand. The oil palm fruits are considered the most efficient oilseed to meet the increased need as they are of relatively high productivity. Average annual growth in world vegetable oil production between 1990 and 2015 was palm oil (7.03%), Rapeseed oil (5.2%), Soybean oil (4.6%) and Sunflower oil (4.4%). Palm oil production was 11 and 63.5 million tons in 1990 and 2015, respectively. Its share in food use grew from 32.5% in 2013 and surpassed 34% by 2015 (Oil World, 2016).

The Malaysian agricultural sector has become one of the pillars of the national economy of Malaysia. The increase in demand for palm oil has resulted in the rapid growth of the agro-industry within Southeast Asian countries, particularly Malaysia who leads the way in production. The Malaysian government has emphasized the development and further expansion of oil palm plantations in its five-year plans in order to make the industry a leading contributor to the growth of the national economy (Otieno et al., 2016).

Another important reason for the Malaysian government's emphasis on the oil palm industry is to use it as an opportunity to reduce the poverty level in rural communities. Towards this end, the rural community has been encouraged to actively participate in the palm oil production activities for additional income and for a better life. The aim of the five-year plans is to increase the industry's gross national income contribution from the present RM 52.7 billion to RM178.0 billion by 2020. On the other hand, the oil palm plantations are currently facing a productivity gap due to various farmers possessing varying farming backgrounds apart from having to face the challenge of change and environmental pollution (Barcelos et al., 2015; MPC ,2017).

Oil palm is widely cultivated in several parts of the country (Otieno et al., 2015). Currently, oil palm is planted on 5.23 million hectares, constituting 15.8% of the total land area and more than 70% of agricultural land in the country (Otieno et al., 2016). Malaysia produces up to 19 million tons of palm oil, with an export of nearly 89% (USDA, 2015). It currently contributes 39% of global palm oil production and 44% of world exports. In terms of total oils and fats, Malaysia's contribution to the global total is 12% of production and 27 % of exports of oils and fats. Ranked among the largest producers and exporters of palm oil and its derived products, Malaysia plays a crucial role in meeting the increasing universal requirement for oils and fats sustainably (Shanmuganathan et al., 2014).

## **1.2 Oil Palm Yield and Energy**

Oil palm provides the highest potential yield per hectare of all sources of vegetable oil. It is capable of producing double the amount of oil compared to rapeseed and almost four times more than soybeans, groundnut and sunflower per hectare per year. As of 2014, the United Nations have estimated that, under the ideal management of high-yield breeding programmers, different varieties of oil palm can produce more than 20 tons of FFBS per ha per year which translates to over five tons of oil per ha per year. About 10% of the dry biomass of the crop comprises of the oils while 90% comprises of cellulosic material and fibre which can be used as second-generation materials for the production of biofuel (Barcelos et al., 2015). In Malaysia, there were 18 biodiesel plants producing a total of 2.34 million ton/yr. Both Johor and Selangor recorded five biodiesel plants operating in 2015, with a total production capacity of 0.99 million tons/yr. for Johor, followed by Selangor with 0.42 million ton/yr. Remaining eight plants with total annual production capacity of 0.92 million tons are located in Pahang, Perak, Sabah and Sarawak (MPOB, 2017).

The 2015 average FFB yield for the estates sector was reported at 18.48 ton/ha, a marginal drop of 0.8 % or 0.15 ton/ha from 18.63 ton/ha registered in 2014. On the other hand, palm oil opening stocks were 2.02 million tons, higher by 1.4% in comparison with the previous year's opening level at 1.99 million tons. Stocks for the first half of 2015 were lower compared to stocks in the second half of 2015, due to lower supply caused by low production from July 2015 onwards (MPOB, 2016).

For the last few years, environmental issues have become increasingly relevant in relation to economic activities and public health, both in Malaysia and globally. A specific concern is the atmospheric environmental problems, which in the past has been ignored in Malaysia but have now emerged as a significant national concern in recent years (Dislich et al., 2017). Globally, air pollution has become a major threat to the health and well-being of humans as well as plant life. Based on the severity of the pollution and also the duration of exposure, air pollution can potentially be significantly unhealthy for humans add in the case of oil palms, negatively affect growth and yield (Kusin et al., 2015).

Energy is the key to agro-processing development in Malaysia. Energy and environment are two sides of the same coin; increasing energy consumption anywhere will be accompanied by increased negative effects on the environment. It is accepted that air pollution, acid rain, and, particularly, global climate change are the inevitable consequences of greenhouse gas emissions from the burning of fossil fuels. Agriculture both produces and subsequently consumes energy. It uses huge supplies of locally available energy, namely, seed, manure and animate energy as direct and indirect energy sources (Eksioglu et al., 2015; Mejjide et al., 2017). The direct energy includes diesel or gasoline fuels, human power, animal energy, fertilisers, and chemicals. Indirect energy is released directly into the source of energy that is not directly put into agricultural activity but released through a conversion process. An example of an indirect source of energy is machinery. Energy input for machinery refers to the energy requirement in producing the machine instead of the energy required to operate the machinery. Energy to operate the machinery can be classified as energy input from human labour (Michaelides, 2012).

It is a priority among designers and planners to develop energy-efficient agricultural systems that require low energy input in comparison with the output of food. This will lower the greenhouse gas emissions from agricultural production systems (Begum & Nazri, 2013; Nabavi-Pelesaraei et al., 2013a).

### **1.3 Genetic Algorithm and Neural Network Hybrid**

In the oil palm industry, modelling and selecting variables play a significant role in the effort to understand different problems. Modelling is employed in decision making, and advances in computer technology have made available novel approaches for studying modelling. While choosing variables is for the purpose of selecting the “best” subset of

predictors or is defined as “finding a set of predictor variables which gives a good fit, predicts the dependent value well and is as small as possible.” It is used to determine the most significant factor affecting agricultural production.

Modelling and selecting variables can be grouped into statistical and heuristic methods. The statistical method is defined as “the analysis of the relationship between multiple measurements made on groups of subjects or objects, with the model usually containing systematic elements and random effects.” Mathematically, statistical modelling can be defined as “a set of probability distributions on the sample space.” Modelling includes the proper application of statistical analysis approaches with specific assumptions on testing the hypothesis, interpreting the data, and drawing a conclusion that can be applied (Kodratoff, 2014). Selection of input variables is an essential and important consideration in determining the ideal functional form of statistical models. The selection of input variables is normal in developing all statistical models and is highly dependent on the discovering relationships within the available data for the identification of appropriate predictors of the model output. Traditionally, logistic regression models are used as the variables selection methods (Sun et al., 2016 a).

The heuristic approach is defined as “pertaining to the use of general knowledge based on experimentation, evaluating possible answers or solutions, or trial-and-error methods relating to solving problems by experience rather than theory and optimisation solving by finding values of the variables that minimise or maximise the objective function while satisfying the constraints. Heuristic also refers to the problem-solving method that requires the conception of a hypothetical answer to a problem at the beginning of an inquiry to provide guidance to the inquiry. The most important types of the heuristic approaches comprise the neural network (NN) model and genetic algorithm (GA), which are based on the rules of thumb and extensively employed in different fields. A very significant feature of neural networks is their adaptive nature where learning by example: substitutes for “programming” in problem-solving. This feature makes these computational approaches very attractive as application domains, where one possesses little or inadequate comprehension of the issue to be addressed, but where training data or examples exist (Asta, 2015).

The notion of a neural network hinges on the human brain, which is made up of billions of neurons interconnected by synapses. In the same manner, NN is composed of many computational units which are also called neurons. The interconnections of the neurons dictate the characteristics of both a brain and a neural network (Da Silva et al., 2017). The feed forward back propagation ANN is a popular method employed to train neural networks. ANN has been widely applied to predict yield, energy consumption, energy demand, environmental problems and solve different types of issues (Chang et al., 2012). Currently, a nonlinear autoregressive NN with exogenous inputs NARX Time series prediction algorithms has been frequently used in several areas, e.g., predicting financial markets, weather forecasting, and complex dynamical system analysis (Khamis & Abdullah, 2014).

GAs are stochastic search approaches that provide guidance to a population of solutions towards an optimum employing the principles of evolution and natural genetics. Recently, GAs have become a popular optimisation tool for several research areas, such as system control, control design, and science and engineering. GAs draw inspiration from the evolution of populations (Mohanta & Sethi, 2011). Algorithms, which combine GAs and NN, have exhibited enhanced convergence properties compared to pure backpropagation. Such hybrid systems can locate the weights and also the architecture of NN, such as a number of layers, the processing elements per layer and the manner in which processing elements are connected. To summarize, GAs has been applied in NNs for three main functions: (i) train the weights of the connections, (ii) design the structure of the network, and (iii) locate an optimal learning rule (Chang et al., 2012; Karimi and Yousefi, 2012).

#### **1.4 Problem Statement**

Over the last decade, the Malaysian oil palm industry has been facing the challenge of the reduced rate of palm oil yield, caused by the sizeable difference between the actual production of palm oil and the crop's genetic potential with high land usage. The gap has grown wider over time. The oil palm yield varies in various areas of Malaysia and is distributed between high yield, medium and worst, which have significantly affected the efficiency of production. In Malaysia, current planting materials are capable of producing 40 tons of FFBS /ha/yr, yielding 6–7 ton of oil. However, the reality shows average yields to be only between 50 to 60% of this potential. In addition to other challenges include, the labour shortage is the most severe constraint, and presently the industry is highly dependent on foreign workers. Furthermore, available land for expansion is limited, particularly in Peninsular Malaysia where land cost is also significantly higher.

The demand for palm oil continues to increase, merely expanding the oil palm plantations is not an advisable response. A viable response would be by way of increasing the output of existing plantations. Modelling in various aspects related to agriculture is important, given the dynamic conditions of oil palm production. Despite the strong need for accurate forecasts, the current status of these predictions is far from satisfactory. No well-defined forecasting method exists that takes into account most of the factors that drive yield. Although there are established models, they tend to be “one size fits all,” and are linear.

The challenge in modelling oil palm yield is due to the fact that it does not follow a linear model. It typically takes a nonlinear growth curve. The function of a growth curve and production have a sigmoid form. In modelling a non-linear curve, the problem becomes more complex when there are additional independent variables. The major hindrance in modelling the behavior of yield and energy consumption are the challenge of extracting the constants of the mathematical models. In light of the complexity of these relationships, traditional data-processing techniques are unable to satisfactorily investigate the process and product parameters because of non-linear relationships

among the variables. Non-linear methods can be used to address this issue as they are powerful predictive tools. One method for modelling non-linear (accommodating multivariate) and non-parametric data is Neural Networks (NNs), which is a model-free estimation. Exploratory research on artificial intelligence has revealed that little has been done on oil palm yield and energy consumption.

The immediate and obvious effect of adding a high number of input variables is that the size of an NN increase, which raises the computational burden related to querying the network - a significant effect in the determination of the training speed. Climatic phenomena, air pollutants, and energy consumption have a direct impact on oil palm production or yield. Environmental change is the most common stressful condition oil-palm faces, so monitoring these related factors is beneficial for the prediction of oil palm yields (Corley and Tinker, 2016; Saadon et al., 2014). Thus, a lot of variables that can lead to maximum oil palm production should be identified. Few studies have focused on this differentiation with focused on a limited number of variables. As such, any of the factors mentioned cannot be randomly ignored as it could have an effect on the prediction accuracy. Selection of the most informative variables or elimination of the uninformative ones could enhance the performance of multivariate calibration models.

Thus, the manner in which variables are selected is deemed an important area of agricultural research. One of the most common methods uses traditional statistics. Although generally understood and easily computed, these methods involve the addition/removal of one variable at a time, based on section. According to Ficken (2015), establishing specific variables that exert considerable effect collectively would be difficult because linear relationships or linear correlations consider only one parameter at a time. The challenges of input variables selection emerge because of (i) the number of available data is huge; (ii) this huge data creates redundancies due to high correlations between potential input variables; and (iii) some variables have slight or no predictive capability. Genetic algorithm which is a tool for computational optimization can be combined with NNs. Specifically, in cases where a large number of potential inputs are available, they can be used to select optimal subsets of inputs for model development.

## **1.5 Research Objectives**

The main objectives of the research are to develop of a hybrid neural networks model with GA-selected inputs for predicting oil palm yield and energy consumption within the multiple areas in Malaysia, based on large-scale climate indices, types of oil palm areas, air pollution and energy consumption. The specific objectives and of the study are as follows:

- 1- To develop a genetic algorithm and Stepwise as input variable selection models to identify the most significant variables that affect the FFB production, palm oil yield and output energy.

- 2- To develop and propose the preferred ANN and NARX architectures, and their hybrids with a genetic algorithm and Stepwise from earlier input variable selection model determinations for the predictions of FFB, palm oil yield and output energy.
- 3- To develop multiple linear regression models (Mathematical Model) to predict FFB, palm oil yield and output energy and compare it with the final NN system.
- 4- To explore the effects of the selected significant variables in the production of FFB, palm oil, and energy that will lead to the maximum the oil palm production in Malaysia.

## 1.6 Scope of the Study

This study focuses on the interactions between climate data including rainfall, rainy days, humidity, radiation, temperature, surface wind speed, evaporation, cloud cover and air pollution data as well as types of oil palm areas data, namely: O3, CO, NO2, SO2, PM10, the percentage of mature area and percentage of the immature area. Additionally, the interactions between input energy data including eight variables: human power, electricity, fuel, water, NPK fertilizers, and seed. This research will cover the years 2005 to 2015 to gain more accurate results on the impact of environmental sources and input energy over the Malaysian states.

The selections of data which need to be used and input for the study will be based on the availability of data from reliable sources. The effect of some important parameters in oil palm yield such as in-situ soil classification, soil moisture content, etc., was not considered in this investigation because these data are not available in a time series format and furthermore the related information may vary from plantation to plantation even though plantations are within the same district. As well as, sometimes the accessibility to the data is almost impossible because these data were classified as confidential.

The establishment of an integrated FFB, PO, and output energy models for the various areas of Malaysia that contain: (i) Determine model inputs that are extremely important via development of two methods, namely GA and Stepwise methods, to improve the intelligent prediction models. (ii) Investigate the effectiveness of two architectures in NNs namely multi-layer feedforward backpropagation (ANN) and nonlinear autoregressive exogenous neural network (NARX). A comparative study will also be performed between the results obtained from the NNs and the results obtained from the multi-regression technique in a statistical approach. A comparative study will be performed between the results obtained from the NNs and the results obtained from the multi-regression technique in a statistical approach. (iii) Select hybrid model criteria by which the performance is evaluated as they can have a significant effect on the model architecture and weight optimization techniques. (iv) Determine a hybrid model architecture including a number of hidden nodes in hidden layers, training algorithms, transfer function, and a number of delays.

Oil palm production models have tested based on the monthly data according to the data classification from the reliable source (MPOB). Finally, the results and finding of this survey will inform the key players in Malaysian oil palm production to know some information about the software's which predicts the oil palm production and output energy. Also, let the are investors in palm oil and smallholders, research centers, industrial manufacturers of oil palm products, distributors and traders of Malaysian oil palm products know that different yields and output energy due to different types of oil palm areas, environmental variables, energy consumption variables, and disparities.

## 1.7 Thesis Layout

The thesis systematically consists of five main parts. Brief descriptions of the content of these chapters are presented below:

*Chapter 1* contains the background of the research, formulation of the problem and problem definition, research objectives, thesis layout has been highlighted and systematics writing.

*Chapter 2* reviews the various literature on the topic. This chapter contains the information necessary to understand the issues discussed in this study. These reviews related to global Importance and Oil palm Production in Malaysia, general view of the environment change and types of oil palm area, the concept of energy and energy sources in Malaysia oil palm. History and background of variables selection and genetic algorithm with stepwise methods, general view of ANN and NARX to problem, prediction and oil palm models.

*Chapter 3* discusses the Methodology, principal and understanding concept of GA, Stepwise, ANN, and NARX. The chapter also explains the process details of the selected variables and application design predictions.

*Chapter 4* contains a discussion on the implementation of the structured analysis and design in Chapter 3. In addition, it discusses the results from the running of the models.

Finally, *Chapter 5* contains the conclusions of the work which has been discussed in previous chapters, especially in Chapter 3 and Chapter 4. The final part of this chapter contains suggestions that were put forward for the continuation of further research.



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## LIST OF PUBLICATIONS

### Journal Articles

Hilal, Y.Y., Ishak, W.I.W., Yahya, A. & Asha'ari, Z. H. (2016) An Artificial Neural Network with Stepwise Method for Modeling and Simulation of Oil Palm Productivity Based on Various Parameters in Sarawak. *Research Journal of Applied Sciences, Engineering, and Technology*, 13(9): 730-740.

Hilal, Y.Y., Ishak, W.I.W., Yahya, A. & Asha'ari, Z. H. (2018) Development of genetic algorithm for optimization of yield models in oil palm production. *Chilean Journal of Agricultural Research* 78(2):228-237.

Hilal, Y.Y., Yahya, A., Ishak, W.I.W., & Asha'ari, Z. H. (2017) A Genetic Algorithm and Mathematical Models to Prediction of Oil Palm Production in Peninsular Malaysia.

Submitted to: *Journal of Agricultural Sciences and Technology* (ISI Q2)

Hilal, Y.Y., Yahya, A., Ishak, W.I.W., & Asha'ari, Z. H. (2018) Develop a Model selection in Oil Palm Production based on Genetic Algorithms.

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Hilal, Y.Y., Yahya, A., Ishak, W.I.W., & Asha'ari, Z. H. (2018) Forecasting Oil Palm Production Based on a Nonlinear Autoregressive Exogenous (NARX) Neural Network Model.

Submitted to: *The Journal of Animal and Plant Sciences* (ISI Q3).

Hilal, Y.Y., Yahya, A., Ishak, W.I.W., & Asha'ari, Z. H. (2018) Development of artificial intelligence to optimization palm oil production models

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