

ABSTRACT

The current method for composition measurement of an industrial distillation column specifically offline method, is slow, tedious and could lead to inaccurate results. Among the advantages of using online composition designed are to overcome the long time delay introduced by laboratory sampling and provide better estimation, which is suitable for online monitoring purposes. Principal component and partial least square analysis are used to determine the important variables surrounding the column prior to implementing the neural network. It is due to the different types of data available for the plant, which requires proper screening in determining the right input variables to the dynamic model. Statistical analysis is used as a model adequacy test for the composition prediction of n-butane and i-butane in the column. Simulation results showed that the Artificial Neural Network (ANN) can reliably predict the online composition of the column. The major contribution of the current research is the development of composition prediction of n-butane and i-butane using equation based neural network (NN) models. Based on statistical analysis, the results indicate that neural network equation, which is more robust in nature, predicts better than the PLS equation and RA equation based methods. The temperature predictions using neural network equation are also compared with partial least square (PLS) and regression analysis (RA) equations methods. A new technique for nonlinear system, which is based on hybrid neural network modeling, is proposed. The hybrid model consists of combination of residual composition and residual temperature with first principle in terms of mass and energy balance. Hybrid neural network equation performs better than the hybrid neural network, and neural network predictions to estimate composition and temperature for the column. The use of an inverse neural network and forward neural network are used for the direct control of a distillation column. The neural network used for the control strategy to track the set point of the top and bottom temperature. Neural network

estimators are used to track the set point of the top and bottom composition together with disturbances. There are two types of controller used for control strategies which are the direct inverse control (DIC) and internal model controller (IMC). Based on the results, IMC and DIC were found to perform better in controlling the temperature with respect to set point changes and disturbances compared to conventional PID controllers.

ABSTRAK

Kaedah semasa untuk mengukur komposisi kolum penyulingan perindustrian kaedah khusus di luar talian, lambat, membosankan dan boleh membawa kepada keputusan yang tidak tepat. Antara kelebihan menggunakan komposisi dalam talian yang direka adalah untuk mengatasi kelewatan masa yang panjang yang diperkenalkan oleh sampel makmal dan memberikan anggaran yang lebih baik, yang sesuai untuk tujuan pemantauan dalam talian. Komponen utama dan sebahagian analisis kuasa dua terkecil yang digunakan untuk menentukan pembolehubah penting sekitar ruang sebelum melaksanakan rangkaian neural. Ia adalah disebabkan oleh pelbagai jenis data yang ada untuk industri, yang memerlukan pemeriksaan yang betul dalam menentukan pembolehubah input yang betul untuk model yang dinamik. Analisis statistik digunakan sebagai ujian kecukupan model ramalan komposisi daripada n-butana dan i-butana dalam ruang. Keputusan simulasi menunjukkan bahawa Rangkaian Neural Buatan (ANN) pasti boleh meramalkan komposisi talian lajur. Sumbangan utama kajian semasa adalah pembangunan ramalan komposisi n-butana dan i-butana menggunakan rangkaian neural (NN) model persamaan berasaskan. Berdasarkan analisis statistik, keputusan menunjukkan bahawa persamaan rangkaian neural, yang lebih teguh dalam alam semula jadi, meramalkan lebih baik daripada persamaan PLS dan persamaan RA kaedah berasaskan. Ramalan suhu menggunakan persamaan rangkaian neural juga berbanding kurangnya separa persegi (PLS) dan analisis regresi (RA) persamaan kaedah. Satu teknik baru untuk sistem tak linear, yang berasaskan pemodelan neural hibrid, adalah dicadangkan. Model hibrid terdiri daripada gabungan komposisi sisa dan sisa suhu dengan prinsip pertama dari segi jisim dan tenaga-kira. Hibrid persamaan rangkaian neural melakukan lebih baik daripada rangkaian neural hibrid, dan ramalan rangkaian neural untuk menganggarkan komposisi dan suhu bagi lajur. Penggunaan rangkaian neural songsang dan rangkaian neural hadapan digunakan untuk kawalan langsung lajur

penyulingan. Rangkaian neural digunakan untuk strategi kawalan untuk mengesan titik set suhu bahagian atas dan bawah. Penganggar rangkaian neural digunakan untuk mengesan titik set komposisi atas dan bawah bersama-sama dengan gangguan. Terdapat dua jenis kawalan yang digunakan untuk strategi kawalan yang kawalan langsung songsang (DIC) dan pengawal model dalaman (IMC). Berdasarkan kepada keputusan, IMC dan DIC didapati prestasi yang lebih baik dalam mengawal suhu berkenaan untuk menetapkan titik perubahan dan gangguan berbanding dengan pengawal PID konvensional

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TABLE OF CONTENTS

Abstract.....	iii
Abstrak	v
Acknowledgement.....	vii
Table of Contents.....	viii
List of Figures.....	xiii
List of Tables.....	xxii
Lis of Symbols and Abbreviations.....	xxiv
List of Appendices	xxvi
CHAPTER 1 : INTRODUCTION.....	1
1.1 Problem statement and motivation.....	2
1.2 Objectives.....	6
1.3 Scope of work.....	7
1.4 Novelty.....	8
1.5 Dissertation organization.....	8
CHAPTER 2 : LITERATURE REVIEW.....	10
2.1 Introduction.....	10
2.2 Neural network introduction.....	10
2.3 Types of artificial neural network.....	11
2.3.1 Feedforward network.....	12
2.3.2 NARX network.....	12
2.4 Learning paradigms learning task.....	12

2.4.1	Supervised learning.....	13
2.4.2	Learning algorithms.....	13
2.4.3	Levenberg-Marquardt method.....	14
2.5	Neural network design.....	15
2.5.1	Procedure for obtaining the neural network models.....	16
2.6	Data pretreatment.....	18
2.6.1	Principal component analysis (PCA).....	18
2.6.2	Partial least square (PLS).....	22
2.6.3	Literature review principal component and partial least square analysis for distillation column.....	24
2.6.4	Literature review modeling for distillation column especially debutaniser column.....	26
2.6.5	Literature review using neural network for distillation column.....	27
2.6.6	Literature review hybrid modeling for chemical processes.....	30
2.6.7	Literature review for control of the distillation column.....	34

CHAPTER 3: PLANT DESCRIPTION AND CASE STUDY OF THE DEBUTANISER COLUMN..... 46

3.1	Introduction.....	46
3.2	Plant description.....	46
3.3	Data generation: open loop, closed loop, extract close loop.....	50
3.4	Steady state and dynamic state.....	52
3.5	Open loop response.....	56
3.5.1	Step test overhead pressure.....	57
3.5.2	Step test reflux flow rate.....	58
3.5.3	Step test reboiler flow rate.....	60

3.5.4	Close loop response.....	61
3.5.5	Validate online and simulation composition in close loop.....	64
3.5.6	Extract from close loop data.....	66
3.6	Data pretreatment principal component analysis and partial least square.....	68
3.6.1	PCA and PLS analysis.....	71

CHAPTER 4 : NEURAL NETWORK PROCESS MODEL FOR COMPOSITION AND TEMPERATURE.....81

4.1	Introduction.....	81
4.2	Methodology for modelling.....	81
4.3	Model adequacy test for neural network to determine the hidden layer.....	83
4.4	Neural network prediction of n-butane composition (MIMO model).....	85
4.4.1	With partition into 3.....	87
4.4.2	Validate based on close loop data for n-butane.....	93
4.5	Model data generation.....	101
4.5.1	Neural network, Partial least square (PLS) and Regression Analysis (RA) data sets.....	101
4.5.2	Neural network n-butane equation based model.....	103
4.5.3	PLS analysis.....	105
4.5.4	Regression analysis.....	105
4.5.5	Analysis of variance (ANOVA) n-butane.....	107
4.5.6	Comparison NN, PLS and RA.....	109
4.5.7	Residual analysis.....	118
4.6	Neural network design.....	120
4.6.1	Neural network top and bottom temperature (MIMO model).....	121
4.7	Neural network, PLS and RA modeling temperature prediction.....	127

4.7.1	Neural network equation based.....	127
4.7.2	PLS model.....	128
4.7.3	Regression model.....	129
4.7.4	Analysis of variance (ANOVA) results for neural network model.....	130
4.7.5	Comparison NN, PLS and RA.....	131
4.7.6	Residual analysis.....	137

CHAPTER 5 : HYBRID NEURAL NETWORK TO ESTIMATE COMPOSITION AND TEMPERATURE FOR THE COLUMN.....140

5.1	Introduction.....	140
5.2	Hybrid model construction.....	141
5.3	Hybrid simulation of the distillation column.....	142
5.4	Mathematical modelling of the distillation column.....	143
5.5	Hybrid neural network (HNN) approach.....	148
5.6	Neural network hybrid modelling.....	149
5.7	Residual neural network n-butane.....	156
5.7.1	With partition into 3.....	158
5.8	Residual top and bottom temperature neural network.....	161
5.8.1	With partition into 3.....	163
5.9	Hybrid modelling of n-butane.....	167

CHAPTER 6 : ADVANCED PROCESS CONTROL.....175

6.1	Introduction.....	175
6.2	Neural network based control strategies.....	177
6.2.1	Direct Inverse Control (DIC) method.....	178
6.2.2	Internal Model Control (IMC) method.....	179

6.2.3	Neural networks models.....	179
6.2.3.1	Forward models.....	179
6.2.3.2	Neural network estimator.....	181
6.2.3.3	Inverse models.....	182
6.3	Neural network development.....	184
6.3.1	Set point changes.....	184
6.3.2	Disturbances test.....	188
	n-butane	
6.3.3	Neural network estimator.....	191
CHAPTER 7 : SUMMARY AND MAJOR CONTRIBUTION.....		196
7.1	Introduction.....	196
7.2	Summary of work.....	196
7.3	Major contribution of this work.....	198
CHAPTER 8 : CONCLUSION AND RECOMMENDATIONS.....		200
8.1	Conclusions.....	200
8.2	Recommendations and future works.....	201
	References.....	203
	List of Publications and Papers Presented.....	211
	Appendix.....	212

LIST OF FIGURES

Figure 2.1: General procedure to obtain the suitable neural network model.....	17
Figure 2.2: Notation used in PCA.....	19
Figure 2.3: A geometric illustration of a PCA model with two principal components t_1 and t_2	21
Figure 2.4: The X variables is defined as factors and Y variables are called responses.	24
Figure 3.1: Flow chart for the refinery process.....	49
Figure 3.2: Debutaniser column configuration.....	50
Figure 3.2a: Simulation flow chart.....	52
Figure 3.2b: Flow chart to extract close loop to obtain open loop data.....	56
Figure 3.3: top temperature.....	57
Figure 3.4: bottom temperature.....	57
Figure 3.5: receiver bottom temperature.....	57
Figure 3.6: light naphtha temperature.....	57
Figure 3.7: reboiler outlet temperature.....	58
Figure 3.8: feed temperature.....	58
Figure 3.9: receiver overhead pressure.....	58
Figure 3.10: top temperature.....	59
Figure 3.11: bottom temperature.....	59
Figure 3.12: receiver bottom temperature.....	59
Figure 3.13: light naphtha temperature.....	59
Figure 3.14: reboiler outlet temperature.....	59
Figure 3.15: feed temperature.....	59
Figure 3.16: receiver overhead pressure.....	59
Figure 3.17: top temperature.....	60
Figure 3.18: bottom temperature.....	60

Figure 3.19: receiver bottom temperature.....	60
Figure 3.20: light naphtha temperature.....	60
Figure 3.21: reboiler outlet temperature.....	61
Figure 3.22: feed temperature.....	61
Figure 3.23: receiver overhead pressure.....	61
Figure 3.24: Process variables of Temp 5 for controller settings based on PID, plant and different set point.....	62
Figure 3.25: Process variables of Flow 1 for controller settings based on PID, plant and different set point.....	63
Figure 3.26: Process variables of Flow 2 for controller settings based on PID, plant and different set point.....	63
Figure 3.27: Process variables of Pressure 1 for controller settings based on PID, plant and different set point.....	64
Figure 3.28: Top composition n-butane.....	65
Figure 3.29: Bottom composition n-butane.....	65
Figure 3.30: Top composition i-butane.....	65
Figure 3.31: Bottom composition i-butane.....	65
Figure 3.32: Temperature 5.....	67
Figure 3.33: Pressure 1.....	67
Figure 3.34: Debutaniser feed.....	67
Figure 3.35: Debutaniser reflux flows.....	67
Figure 3.36: Manipulated variable Debutaniser.....	68
Figure 3.37: Manipulated variable reflux flow rate.....	68
Figure 3.38: Manipulated variable reboiler flow rate.....	68
Figure 3.39: Manipulated variable overhead pressure flow rate.....	68
Figure 3.40: Model window for PCA in SIMCA-P environment.....	70

Figure 3.41: Component contribution plot overhead pressure flow rate.....	73
Figure 3.42: PLS i-butane.....	73
Figure 3.43: PLS n-butane.....	73
Figure 3.44: Component contribution plot reboiler flow rate.....	74
Figure 3.45: PLS i-butane.....	75
Figure 3.46: PLS n-butane.....	75
Figure 3.47: Component contribution plot reflux flow rate.....	76
Figure 3.48: PLS i-butane.....	76
Figure 3.49: PLS n-butane.....	76
Figure 3.50: Component contribution i-butane.....	77
Figure 3.51: PLS i-butane.....	77
Figure 3.52: Component contribution n-butane.....	78
Figure 3.53: PLS n-butane.....	78
Figure 4.1: Neural network architecture for n-butane.....	86
Figure 4.2: Profile of the RMSE of n-butane training.....	87
Figure 4.3: Profile of the RMSE of n-butane validation.....	87
Figure 4.4: Profile of the RMSE of n-butane testing.....	87
Figure 4.5: Actual and simulated n-butane top composition training.....	88
Figure 4.6: Actual and simulated n-butane bottom composition training.....	88
Figure 4.7: Actual and simulated n-butane top composition validation.....	88
Figure 4.8: Actual and simulated n-butane bottom composition validation.....	88
Figure 4.9: Actual and simulated n-butane top composition testing.....	89
Figure 4.10: Actual and simulated n-butane bottom composition testing.....	89
Figure 4.11: Actual and simulated n-butane top composition line plot training.....	89
Figure 4.12: Actual and simulated n-butane bottom composition line plot training.....	89
Figure 4.13: Actual and simulated n-butane top composition line plot validation.....	90

Figure 4.14: Actual and simulated n-butane bottom composition line plot validation...	90
Figure 4.15: Actual and simulated n-butane top composition line plot testing.....	90
Figure 4.16: Actual and simulated n-butane bottom composition line plot testing.....	90
Figure 4.17: Manipulated variable reboiler and reflux flow rate.....	90
Figure 4.18: Actual and simulated n-butane top composition training.....	94
Figure 4.19: Actual and simulated n-butane bottom composition training.....	94
Figure 4.20: Actual and simulated n-butane top composition validation.....	94
Figure 4.21: Actual and simulated n-butane bottom composition validation.....	94
Figure 4.22: Actual and simulated n-butane top composition testing.....	95
Figure 4.23: Actual and simulated n-butane bottom composition testing.....	95
Figure 4.24: Actual and simulated n-butane top composition line plot training.....	95
Figure 4.25: Actual and simulated n-butane bottom composition line plot training.....	95
Figure 4.26: Actual and simulated n-butane top composition line plot validation.....	96
Figure 4.27: Actual and simulated n-butane bottom composition line plot validation...	96
Figure 4.28: Actual and simulated n-butane top composition line plot testing.....	96
Figure 4.29: Actual and simulated n-butane bottom composition line plot testing.....	96
Figure. 4.30: Prediction versus actual value neural network equation top composition n-butane.....	110
Figure. 4.31: Prediction and actual value for top composition n-butane line plot.....	111
Figure 4.32: Prediction versus actual value neural network equation bottom composition n-butane.....	112
Figure. 4.33: Prediction and actual value for bottom composition n-butane line plot..	112
Figure. 4.34: Prediction versus actual value PLS equation top composition n-butane.	113
Figure. 4.35: Prediction and actual value for top composition n-butane line plot.....	113
Figure. 4.36: Prediction versus actual value PLS equation bottom position n-butane..	114
Figure. 4.37: Prediction and actual value for bottom composition n-butane line plot..	115

Figure. 4.38: Prediction versus actual value RA equation top composition n-butane...	115
Figure. 4.39: Prediction and actual value for top composition n-butane line plot.....	116
Figure. 4.40: Prediction versus actual value RA equation bottom composition n-butane.....	117
Figure 4.41: Prediction and actual value for bottom composition n-butane line plot...	117
Figure 4.42: Residual analysis for neural network equation, PLS equation and regression analysis equation top composition n-butane.....	119
Figure 4.43: Residual analysis for neural network equation, PLS equation and regression analysis equation bottom composition n-butane.....	119
Figure 4.44: Neural network architecture for top and bottom temperature.....	121
Figure 4.45: Profile of the RMSE training.....	122
Figure 4.46: Profile of the RMSE validation.....	123
Figure 4.47: Profile of the RMSE testing.....	123
Figure 4.48: Actual and simulated top temperature training.....	123
Figure 4.49: Actual and simulated bottom temperature training.....	123
Figure 4.50: Actual and simulated top temperature validation.....	124
Figure 4.51: Actual and simulated bottom temperature validation.....	124
Figure 4.52: Actual and simulated top temperature testing.....	124
Figure 4.53: Actual and simulated bottom temperature testing.....	124
Figure 4.54: Actual and simulated top composition line plot training.....	124
Figure 4.55: Actual and simulated bottom composition line plot training.....	124
Figure 4.56: Actual and simulated top temperature line plot validation.....	125
Figure 4.57: Actual and simulated bottom temperature line plot validation.....	125
Figure 4.58: Actual and simulated top temperature line plot testing.....	125
Figure 4.59: Actual and simulated bottom temperature line plot testing.....	125
Figure. 4.60: Prediction versus actual value neural network equation top temperature.....	131

Figure. 4.61: Prediction and actual value for top temperature line plot.....	132
Figure. 4.62: Prediction versus actual value neural network equation bottom temperature.....	132
Figure. 4.63: Prediction and actual value for bottom temperature line plot.....	133
Figure. 4.64: Prediction versus actual value PLS equation top temperature.....	133
Figure. 4.65: Prediction and actual value for top temperature line plot.....	134
Figure. 4.66: Prediction versus actual value PLS equation bottom temperature.....	134
Figure. 4.67: Prediction and actual value for bottom temperature line plot.....	135
Figure 4.68: Prediction versus actual value RA equation top temperature.....	135
Figure. 4.69: Prediction and actual value for top temperature line plot.....	136
Figure. 4.70: Prediction versus actual value RA equation bottom temperature.....	136
Figure 4.71: Prediction and actual value for bottom temperature line plot.....	137
Figure 4.72: Residual analysis for neural network equation, PLS equation and regression analysis equation top temperature.....	138
Figure 4.73: Residual analysis for neural network equation, PLS equation and regression analysis equation bottom temperature.....	138
Figure 5.1: Two approaches used in HNN with FPM.....	142
Figure 5.2: Hybrid model for the composition n-butane and temperature.....	156
Figure 5.3: Neural network architecture for residual n-butane.....	157
Figure 5.4: Profile of the RMSE of n-butane training.....	158
Figure 5.5: Profile of the RMSE of n-butane validation.....	158
Figure 5.6: Profile of the RMSE of n-butane testing.....	158
Figure 5.7: Actual and simulated n-butane top residual composition training.....	159
Figure 5.8: Actual and simulated n-butane bottom residual composition training.....	159
Figure 5.9: Actual and simulated n-butane top residual composition validation.....	159
Figure 5.10: Actual and simulated n-butane bottom residual composition validation..	159

Figure 5.11: Actual and simulated n-butane top residual composition testing.....	159
Figure 5.12: Actual and simulated n-butane bottom residual composition testing.....	159
Figure 5.13: Actual and simulated n-butane top composition line plot training.....	160
Figure 5.14: Actual and simulated n-butane bottom composition line plot training.....	160
Figure 5.15: Actual and simulated n-butane top residual composition line plot validation.....	160
Figure 5.16: Actual and simulated n-butane bottom residual composition line plot validation.....	160
Figure 5.17: Actual and simulated n-butane top residual composition line plot testing.....	161
Figure 5.18: Actual and simulated n-butane bottom residual composition line plot testing.....	161
Figure 5.19: Neural network architecture for residual top and bottom temperature....	162
Figure 5.20: Profile of the RMSE training.....	163
Figure 5.21: Profile of the RMSE validation.....	164
Figure 5.22: Profile of the RMSE testing.....	164
Figure 5.23: Actual and simulated top residual temperature training.....	164
Figure 5.24: Actual and simulated bottom residual temperature training.....	164
Figure 5.25: Actual and simulated top residual temperature validation.....	165
Figure 5.26: Actual and simulated bottom residual temperature validation.....	165
Figure 5.27: Actual and simulated top residual temperature testing.....	165
Figure 5.28: Actual and simulated bottom residual temperature testing.....	165
Figure 5.29: Actual and simulated top residual composition line plot training.....	166
Figure 5.30: Actual and simulated bottom residual composition line plot training.....	166
Figure 5.31: Actual and simulated top residual temperature line plot validation.....	166
Figure 5.32: Actual and simulated bottom residual temperature line plot validation.....	166

Figure 5.33: Actual and simulated top residual temperature line plot testing.....	167
Figure 5.34: Actual and simulated bottom residual temperature line plot testing.....	167
Figure 5.35: Top composition n-butane first principle model.....	168
Figure 5.36: Bottom composition n-butane first principle model.....	168
Figure 5.37: Top temperature first principle model.....	169
Figure 5.38: Bottom temperature first principle model.....	169
Figure 5.39: Hybrid model, neural network and actual top composition n-butane.....	170
Figure 5.40: Hybrid model, neural network and actual bottom composition n-butane.....	170
Figure 5.41: Hybrid model, neural network and actual top temperature.....	172
Figure 5.42: Hybrid model, neural network and actual bottom temperature.....	172
Figure 6.1: Control loop of neural network based Direct Inverse Model Control (DIC).....	177
Figure 6.2: Control loop of neural network based Internal Model Controller (IMC).....	178
Figure 6.2a: Forward and inverse models to control temperature.....	183
Figure 6.3: Set point top temperature.....	186
Figure 6.4: Set point bottom temperature.....	186
Figure 6.5: Manipulated variable temperature neural network.....	187
Figure 6.6: Manipulated variable temperature PID.....	187
Figure 6.7: Disturbances top temperature.....	189
Figure 6.8: Disturbances bottom temperature.....	189
Figure 6.9: Manipulated variable temperature neural network disturbances.....	190
Figure 6.10: Manipulated variable temperature PID disturbances.....	190
Figure 6.11: Neural network estimator for the top composition.....	191
Figure 6.12: Neural network estimator for the bottom composition.....	192
Figure 6.13: Manipulated variable composition for PID.....	192
Figure 6.14: Top composition disturbances.....	193
Figure 6.15: Bottom composition disturbances.....	194

Figure 6.16: Manipulated variable composition PID due to disturbances.....	194
Figure 6.17 Steady state error top temperature.....	194
Figure 6.18 Steady state error bottom temperature.....	195

LIST OF TABLES

Table 3.1: Debutaniser column specification.....	48
Table 3.2: Tag name description of the column.....	49
Table 3.3: Composition at the feed.....	53
Table 3.4: Properties of the compounds.....	53
Table 3.5: Controller setting and set point.....	54
Table 3.6: Important variables involved in the PCA analysis.....	70
Table 3.7: Data pretreatment after PCA and PLS.....	77
Table 3.8: Data pretreatment after PCA and PLS.....	78
Table 3.9: Important variables for neural network prediction of n-butane.....	79
Table 3.10: Important variables for neural network prediction of i-butane.....	79
Table 4.1: Important variables for neural network prediction.....	85
Table 4.2: Neural network architecture.....	86
Table 4.3: Statistical analysis for n-butane composition prediction.....	92
Table 4.4: Statistical analysis for online n-butane composition prediction.....	97
Table 4.5: ANOVA of the n-butane top composition.....	108
Table 4.6: ANOVA of n-butane bottom composition.....	109
Table 4.7: Variables involved in the PLS analysis, regression analysis and neural network n-butane.....	110
Table 4.8: n-butane statistical analysis of NN equation, PLS equation and RA equation.....	118
Table 4.9: Important variables for neural network prediction.....	121
Table 4.10: Neural network architecture.....	122
Table 4.11: Statistical analysis for temperature with 3 partition.....	126
Table 4.12: ANOVA of the n-butane top temperature.....	130
Table 4.13: ANOVA of n-butane bottom temperature.....	130

Table 4.14: Variables involved in the PLS analysis, regression analysis and neural Network.....	131
Table 4.15: Statistical analysis of NN equation, PLS equation and RA equation.....	137
Table 5.1: Important variables for neural network prediction.....	156
Table 5.2: Neural network architecture.....	157
Table 5.3: Important variables for neural network prediction.....	162
Table 5.4: Neural network architecture.....	163
Table 5.5: Statistical analysis for composition prediction n-butane.....	171
Table 5.6: Statistical analysis for temperature prediction.....	172
Table 5.7: Statistical analysis for robustness analysis variable Temp 6.....	174
Table 6.1:PID tuning.....	185
Table 6.2: Controller performance during set point changes.....	185
Table 6.3: Controller performance during disturbance changes.....	188
Table 6.4: Computing time.....	195

LIST OF SYMBOLS AND ABBREVIATIONS

AIC	:	Akaike information criterion
ANN	:	Artificial neural network
ANOVA	:	Analysis of variance
BIC	:	Bayesian information criteria
CDC	:	Correct Directional Change
IAE	:	Integral absolute error
ISE	:	Integral square of error
LM	:	Levenberg-Marquardt
MAPE	:	Mean Absolute Percentage Error
MS	:	Mean of square
NARX	:	Nonlinear autoregressive network with exogenous inputs
PCA	:	Principal component analysis
PLS	:	Partial least square
R^2	:	Coefficient of determination
RMSE	:	Root Mean Square Error
SS	:	Sum of square
A_t	:	Actual value
C_p	:	Person correlation co-efficient
D_i	:	Product $y_i \times \overline{y_i}$
E_a	:	Actual value
E_p	:	Predicted value
$\overline{E_a}$	:	Average actual value
$\overline{E_p}$	:	Average predicted value
F_t	:	Predicted value
K	:	Number of free model parameters
MSE	:	Mean square error
N	:	Number of observation
R^2	:	R squared
T	:	Number of parameters
df	:	Degree of freedom
F	:	Statistical F value
$x_{measured}$	:	Measure value
$x_{predicted}$	:	Predicted

y_i	:	Difference actual and average actual
$\overline{y_i}$	:	Difference predicted and average predicted
σ^2	:	Variance

LIST OF APPENDICES

Appendix 1.1: Results for i-butane.....	213
Appendix 1.2: Neural network programming.....	245