

REFERENCES

- Basheer, I. A., and Hajmeer, M., Artificial neural networks: fundamentals, computing, design, and application. Journal of Microbiological Methods 43, 2000: 3-31.
- Boston, J. F., Britt, H. J., Jiraponghan, S., and Shah, V. B., An advanced system for simulation of batch distillation operations. Found. Comput.-Aided Chem. Process Des. 2, 1981: 203-237.
- Chen, J., Yea, Y., and Wang, C. W., Neural network model predictive control for nonlinear MIMO processes with unmeasured disturbances. J. Chem. Eng. Japan. 35, 2002: 150-159.
- Converse, A. O., and Gross, G. D., Optimal distillate-rate policy in batch distillation. Ind. Eng. Chem. Fundam. 2, 1963: 217-221.
- Distefano, G. P., Mathematical modeling and numerical integration of multicomponent batch distillation equations. AIChE J. 14, 1968: 190-199.
- Diwekar, U. M., Unified approach to solving optimal design-control problem in batch distillation. AIChE J. 38, 1992: 1551-1563.
- Diwekar, U. M., and Madhavan, K. P., Multicomponent batch distillation column design. Ind. Eng. Chem. Res. 30, 1991: 713-721.
- Eaton, J. W., and Rawling, J. B., Model-Predictive Control of chemical process. Chem. Eng. Sci. 47, 1992: 705-720.
- Farhat, S., Czernicki, M., Pibouleau, L., and Domenech, S., Optimization of multi-fraction batch distillation by nonlinear programming. AIChE J., 36, 1990: 1349-1360.
- Georgieva, P., and Foyo de Azevedo, S., Neural network-based control strategies applied to a fed-batch crystallization process. IJCI. 3, 2006: 224-233.

- Gupta, M. M., Jin, L., and Homma, N., Static and dynamic neural networks: from fundamentals to advanced theory. John Wiley & Sons, Canada, 2003.
- Hagan, M. T., Deamuth, H. B., and Beale, M., Neural network design. PWS, Boston, 1996.
- Hansen, T. T., and Jorgensen, S. B., Optimal control of binary batch distillation in tray or packed column. Chem. Eng. J. 33, 1986: 151-155.
- Jha, S. K., and Madras, G., Neural network modeling of adsorption equilibria of mixtures in supercritical. Ind. Eng. Chem. Res. 44, 2005: 7038-7041.
- Kerkhof, L. H. J., Vissers, H. J. M., On the profit of optimum control in batch distillation. Chem. Eng. Sci. 33, 1978: 961-970.
- Kittisupakorn, P., Hussain, M. A., and Petcherdsak, J., Studies on the use of neural networks in nonlinear control strategies. Journal of Chemical Engineering of Japan. 34, 2001: 453-465.
- Kittisupakorn, P., Tangteerasunun, P., and Thitiyasook, P., Dynamic neural network modeling for hydrochloric acid recovery process. Korean J. Chem. Eng. 22, 2005: 813-821.
- Lee, J. H., Extended Kalman filter based nonlinear model predictive control. Ind. Eng. Chem. Res. 33, 1994: 1530-1541.
- Logsdon, J. S., and Biegler, L. T., Accurate determination of optimal reflux policies for maximum distillate problem in batch distillation. Ind. Eng. Chem. Res. 32, 1993: 692-700.
- Logsdon, J. S., Diwekar, U. M., and Biegler, L. T., On the simultaneous optimal design and operation of batch distillation columns. Chem. Eng. Des. Res. 68, 1990: 434-444.

- Meadows, E. L., Multicomponent batch distillation calculations on a digital computer. Chem. Eng. Prog. Symp. Ser., 59, 1963: 48.
- Mujtaba, I. M., and Macchietto, S., Holdup issues in batch distillation binary mixture. Chem. Eng. Sci. 53, 1998: 2519.
- Mujataba, I. M., Batch distillation: design and operation. Imperial College Press, London, Vol. 3, 2004.
- Nad, M., and Spiegel, L., Simulation of batch distillation by computer and comparison with experiment. Proceedings CEF 87. Sicily, Italy, April, 1987: 737.
- Patwardhan, A. A., Edgar, and Thomas, F., Nonlinear model predictive control of a packed distillation column. Ind. Eng. Chem. Res. 32, 1993: 2345-2356.
- Psichogios, D. M., and Ungar, L. H., Direct and indirect model based control using artificial neural networks. Ind. Eng. Chem. Res. 30, 1991.
- Quintero Marmol, E., Luyben, W. L., and Georgakis, C., Application of extended Luenverger observer to the control of multicomponent batch distillation. Ind. Chem. Eng. Res. 30, 1991: 1870-1880.
- Robinson, E. R., The optimization of batch distillation operations. Chem. Eng. Sci. 24, 1969: 1661-1668.
- Rohani, S., Haeri, M., and Wood, H. C., Modeling and control of a continuous crystallization process Part. 2 model predictive control. Comp. Chem. Eng. 23, 1999: 279-286.
- Seborg, D. E., Edgar, T. F., and Mellichamp, D. A., Process dynamics and control. John Willey & Sons. USA, 1989.
- Schwarm, A. T., and Nikolaou, M., Chance-constrained model predictive control. AIChE J. 45, 1999: 1743-1752.

- Shene, C., Diez, C., and Bravo, S., Neural networks for the prediction of the state of *Zymomonas mobilis* CP4 batch fermentations. Comp. Chem. Eng. 23, 1999: 1097-1108.
- Smith, J. M., Van Ness, H. C., and Abbott, M. M., Introduction to chemical engineering thermodynamics. McGraw-Hill, sixth edition, Singapore, 2001.
- Song, J. J., and Park, S., Neural model predictive control for nonlinear chemical processes. J. Chem. Eng. Japan. 26, 1993: 347-354.
- Temeng, K. O., Schnelle, P. D., and McAvoy, T. J., Model predictive control of an industrial packed bed reactor using neural networks. J. Proc. Contr. 5, 1995.
- Tongmeesee, S., Model-Based control and estimation for free radical polymerization reactor. Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2000.
- Zamproga, E., Barolo, M., and Seborg, D. E. Optimal selection of soft sensor inputs for batch distillation columns using principle component analysis. J. Proc. Contr., 15, 2005: 39-52
- Zupan, J., and Gasteiger, J., Neural networks for chemists: an introduction. VCH, New York, 1993.

APPENDICE

APPENDIX A

MATHEMATICAL MODEL

This chapter presents a rigorous model of conventional batch distillation which Meadows (1963), Distefano (1968), Boston et. al (1980), Mujtaba and Macchietto (1998) used in their simulation and optimization studies.

A.1 Assumptions

The mathematical model is formulated on the assumptions which are listed below.

- The conventional batch distillation column with theoretical plates is used.
- The ideal phase equilibrium model is used.
- The operating pressure is constant.
- The liquid mixtures are introduced at its boiling point. bubble point.
- The liquid and the vapor on plates are perfect mixing.
- The molar liquid holdup on plates and condenser are constant.
- The vapor holdup is neglected.
- The adiabatic column is used.
- The energy dynamic is fast.
- The total condensation without sub-cooling is used.

A.2 Mass and Energy Balance

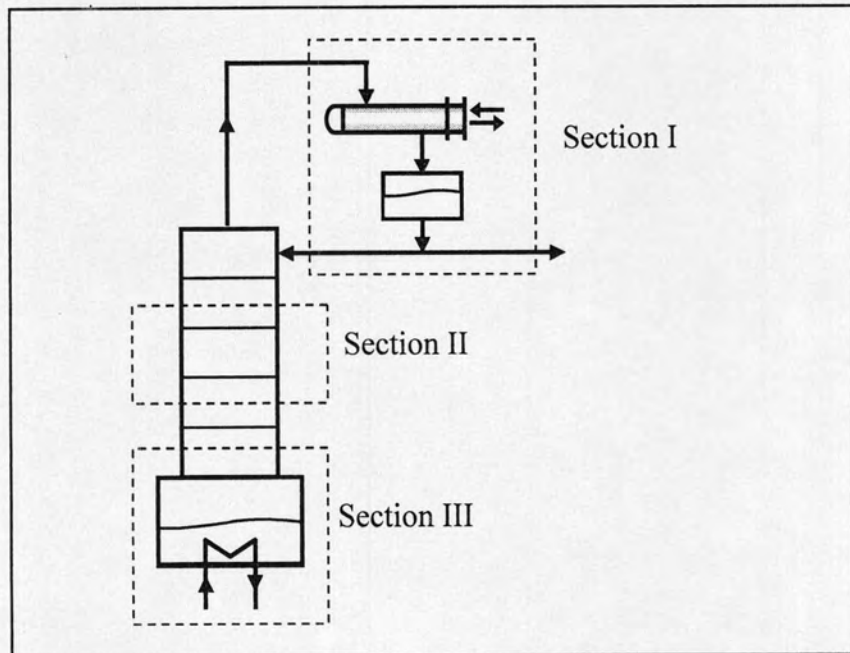


Figure A.1 The three sections of a batch distillation column for material and energy balance calculation

The model equations are presented in three sections as shows in Figure A.1. First section is the equations for the condenser. Then the equations for the plates in the column and the reboiler are presented in the final section. The trays are counted from the top to the bottom.

A.2.1 Section I : The condenser ($n = 1$)

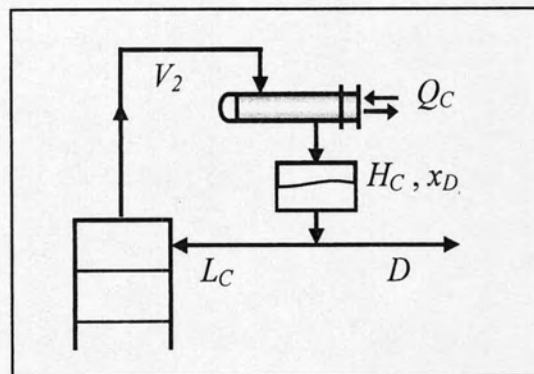


Figure A.2 Material balance diagrams for the condenser

Total mass balance:

$$\frac{dH_C}{dt} = V_2 - L_C - D \quad (\text{A.1})$$

$$L_C = V_1 - D - \delta_t H_C \quad (\text{A.2})$$

$\delta_t H_C$ is calculated using a numerical approximation to the derivative of dH_C / dt .

Component mass balance:

$$\frac{d(H_C x_D)}{dt} = V_2 y_2 - L_C x_D - D x_D \quad (\text{A.3})$$

Using equation (A.1) in equation (A.2) results in

$$\frac{dx_D}{dt} = \frac{V_2}{H_C} (y_2 - x_D) \quad (\text{A.4})$$

Energy balance:

$$\frac{d(H_C h_C^L)}{dt} = V_2 h_2^V - (L_C + D) h_C^L - Q_C \quad (\text{A.5})$$

Using equation (A.1) in equation (A.4) results in

$$\frac{dh_C^L}{dt} = \frac{1}{H_C} [V_2 (h_2^V - h_C^L) - Q_C] \quad (\text{A.6})$$

$$Q_C = V_2 (h_2^V - h_C^L) - H_C \delta_t h_C^L \quad (\text{A.7})$$

$\delta_t h_C^L$ is calculated using a numerical approximation to the derivative of dh_C^L / dt .

A.2.2 Section II : An arbitrary plate n ($2 \leq n \leq (N_p - 1)$)

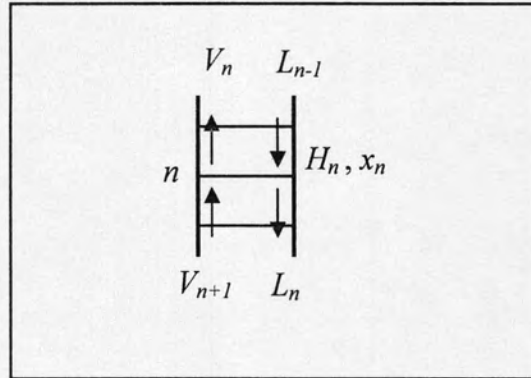


Figure A.3 Material balance diagrams for an arbitrary plate n

Total mass balance:

$$\frac{dH_n}{dt} = V_{n+1} + L_{n-1} - V_n - L_n \quad (\text{A.8})$$

$$L_n = V_{n+1} + L_{n-1} - V_n - \delta_t H_n \quad (\text{A.9})$$

$\delta_t H_n$ is calculated using a numerical approximation to the derivative of dH_n / dt .

Component mass balance:

$$\frac{d(H_n x_n)}{dt} = V_{n+1} y_{n+1} + L_{n-1} x_{n-1} - V_n y_n - L_n x_n \quad (\text{A.10})$$

Using equation (A.6) in equation (A.7) results in

$$\frac{dx_n}{dt} = \frac{1}{H_n} [V_{n+1} (y_{n+1} - x_n) + L_{n-1} (x_{n-1} - x_n) - V_n (y_n - x_n)] \quad (\text{A.11})$$

Energy balance:

$$\frac{d(H_n h_n^L)}{dt} = V_{n+1} h_{n+1}^V + L_{n-1} h_{n-1}^L - V_n h_n^V - L_n h_n^L \quad (\text{A.12})$$

Using equation (A.6) in equation (A.9) results in

$$\frac{dh_n^L}{dt} = \frac{1}{H_n} [V_{n+1}(h_{n+1}^V - h_n^L) - V_n(h_n^V - h_n^L) + L_{n-1}(h_{n-1}^L - h_n^L)] \quad (\text{A.13})$$

$$V_{n+1} = \frac{1}{h_{n+1}^V - h_n^L} [V_n(h_n^V - h_n^L) - L_{n-1}(h_{n-1}^L - h_n^L) + H_n \delta_t h_n^L] \quad (\text{A.14})$$

$\delta_t h_n^L$ is calculated using a numerical approximation to the derivative of dh_n^L / dt .

A.2.3 Section III : The reboiler ($n = N_p$)

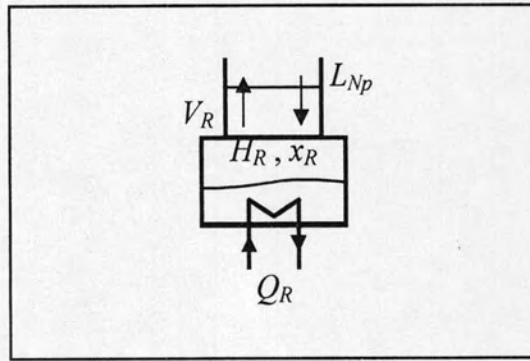


Figure A.4 Material balance diagrams for the reboiler.

Total mass balance:

$$\frac{dH_R}{dt} = L_{N_p-1} - V_R \quad (\text{A.15})$$

Component mass balance:

$$\frac{d(H_R x_R)}{dt} = -V_R y_R + L_{N_p-1} x_{N_p-1} \quad (\text{A.16})$$

Using equation (A.11) in equation (A.12) results in

$$\frac{dx_R}{dt} = \frac{1}{H_R} [-V_R (y_R - x_R) + L_{N_p-1} (x_{N_p-1} - x_R)] \quad (\text{A.17})$$

Energy balance:

$$\frac{d(H_R h_R^L)}{dt} = -V_R h_R^V + L_{N_p-1} h_{N_p-1}^L + Q_R \quad (\text{A.18})$$

Using equation (A.11) in equation (A.14) results in

$$\frac{dh_R^L}{dt} = \frac{I}{H_R} \left[-V_R(h_R^V - h_R^L) + L_{N_p-1}(h_{N_p-1}^L - h_R^L) + Q_R \right] \quad (\text{A.19})$$

$$Q_R = V_R(h_R^V - h_R^L) - L_{N_p-1}(h_{N_p-1}^L - h_R^L) + H_R \delta_t h_R^L \quad (\text{A.20})$$

$\delta_t h_R^L$ is calculated using a numerical approximation to the derivative of dh_R^L / dt .

A.2.4 Summation equation

Liquid-phase mole fraction:

$$\sum_{i=1}^{N_C} x_{i,n} = 1 \quad (\text{A.21})$$

where x_i is a liquid-phase mole fraction, and N_C is the number of components.

Vapor-phase mole fraction:

$$\sum_{i=1}^{N_C} y_{i,n} = 1 \quad (\text{A.22})$$

where y_i is a vapor-phase mole fraction, and N_C is the number of components.

A.3 Thermodynamic and Physical Properties

The thermodynamic and physical properties are used in mathematical model that are:

A.3.1 Vapor liquid equilibrium (VLE)

The goal of vapor liquid equilibrium is to find by calculation the temperature and compositions of phases in equilibrium. The simple model of vapor liquid equilibrium which is based on *Raoult's law* is used in this work. The two main assumptions for VLE calculation are: the vapor phase is an *ideal gas* and the liquid phase is an *ideal solution*.

The mathematical expression which reflects the two above assumptions and which gives quantitative expression to Raoult's law is

$$y_i P = x_i P_i^{SAT} \quad (A.23)$$

where x_i is a liquid-phase mole fraction, y_i is a vapor-phase mole fraction, and P_i^{sat} is the vapor pressure of pure species i at the temperature of the system.

Because Equation A.22, the equation may be summed to give:

$$\sum_i \frac{x_i P_i^{SAT}}{P} = 1 \quad (A.24)$$

Solved for P, they become:

$$P = \sum_i x_i P_i^{SAT} \quad (A.25)$$

Multiply the right side of Equation A. 25 by P_h^{SAT} (outside the summation), dividing by P_h^{SAT} (inside the summation), and solving for the P_h^{SAT} appearing outside the summation gives:

$$P_h^{SAT} = \frac{P}{\sum_i x_i (P_i^{SAT} / P_h^{SAT})} \quad (A.26)$$

The summations are over all species including h, which is an arbitrarily selected species.

A.3.2 Enthalpy equations

Since the mathematical model involves heat balances, it requires values of the liquid and vapor enthalpies throughout column. The enthalpy of ideal vapor mixture and liquid mixture are calculated with

$$h^L = \sum_{i=1}^{N_C} (x_i h_i^L) \quad (A.27)$$

$$h^V = \sum_{i=1}^{N_C} (y_i h_i^V) \quad (A.28)$$

where h^L is the enthalpy of liquid mixture, x_i is a liquid-phase mole fraction, and h_i^L is the pure species enthalpy of liquid mixture, h^V is the enthalpy of ideal vapor mixture, y_i is a vapor-phase mole fraction, and h_i^V is the pure species enthalpy of vapor mixture.

In the vapor phase, the enthalpy of pure species i in the ideal gas state at temperature T is calculated with the standard enthalpy of formation at 298 K ($\Delta H_{298,i}^\circ$) and the heat capacity.

$$h_i^V = \Delta H_{298,i}^\circ + \int_{298}^T C_{p,i} dT \quad (\text{A.29})$$

For the enthalpy of pure species i in liquid phases (h_i^L), the calculation is done with the individual enthalpy in vapor phase deduct the individual enthalpies of vaporization ($\Delta HV_{298,i}$).

$$h_i^L = h_i^V - \Delta HV_{298,i} \quad (\text{A.30})$$

A.3.3 Ideal vapor heat capacity

$$C_{p,i} = A + BT + CT^2 + DT^3 + ET^4 \quad (\text{A.31})$$

where $C_{p,i}$ is a heat capacity of ideal vapor (J/mol·K), T is a temperature (K), A , B , C , D , and E are regression coefficients for chemical compound which show in Table C.2.

A.3.4 Enthalpy of formation

$$\Delta H^\circ = A + BT + CT^2 \quad (\text{A.32})$$

where ΔH° is a enthalpy of formation of ideal gas (kJ/mol), T is a temperature (K), A , B , and C are regression coefficients for chemical compound which show in Table C.3

A.3.5 Enthalpy of vaporization

$$\Delta HV_{298,i} = A \left(1 - \frac{T}{T_c} \right)^n \quad (\text{A.33})$$

where $\Delta HV_{298,i}$ is a enthalpy of vaporization (kJ/mol), T is a temperature (K), T_c is a critical temperature (K), A and n are regression coefficients for chemical compound which show in Table C.4.

A.3.6 Vapor pressure model

$$\log_{10} P^{SAT} = A + (B/T) + (C \log_{10} T) + DT + ET^2 \quad (\text{A.34})$$

where P^{SAT} is a vapor pressure (mmHg), T is a temperature (K), A , B , C , D , and E are regression coefficients for chemical compound which show in Table C.5.

A.4 Calculation Algorithm

For the calculation of BD process by mathematical model can be illustrated as shown in Figure A.5 and A.6.

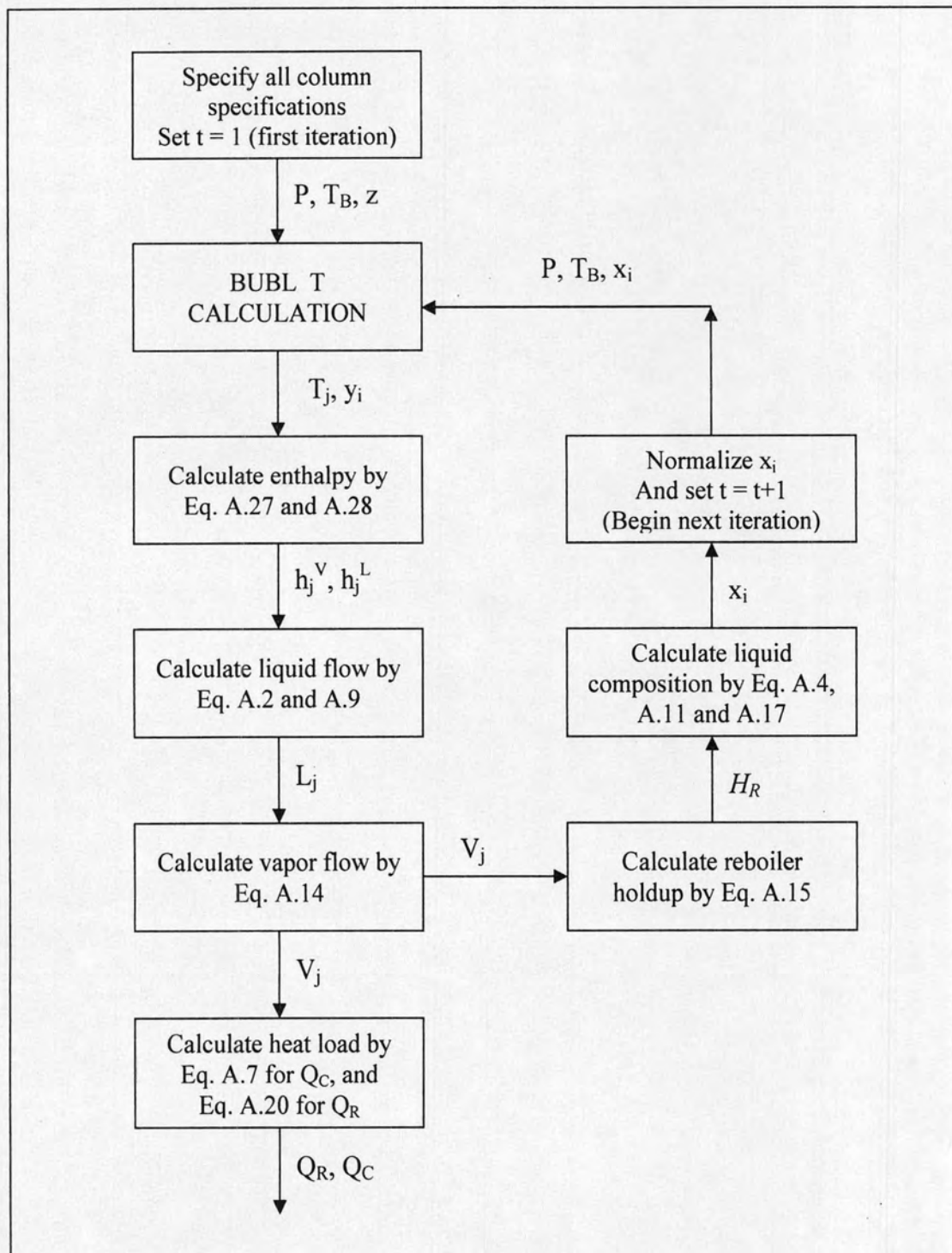


Figure A.5 Block diagrams for the calculation BUBL T

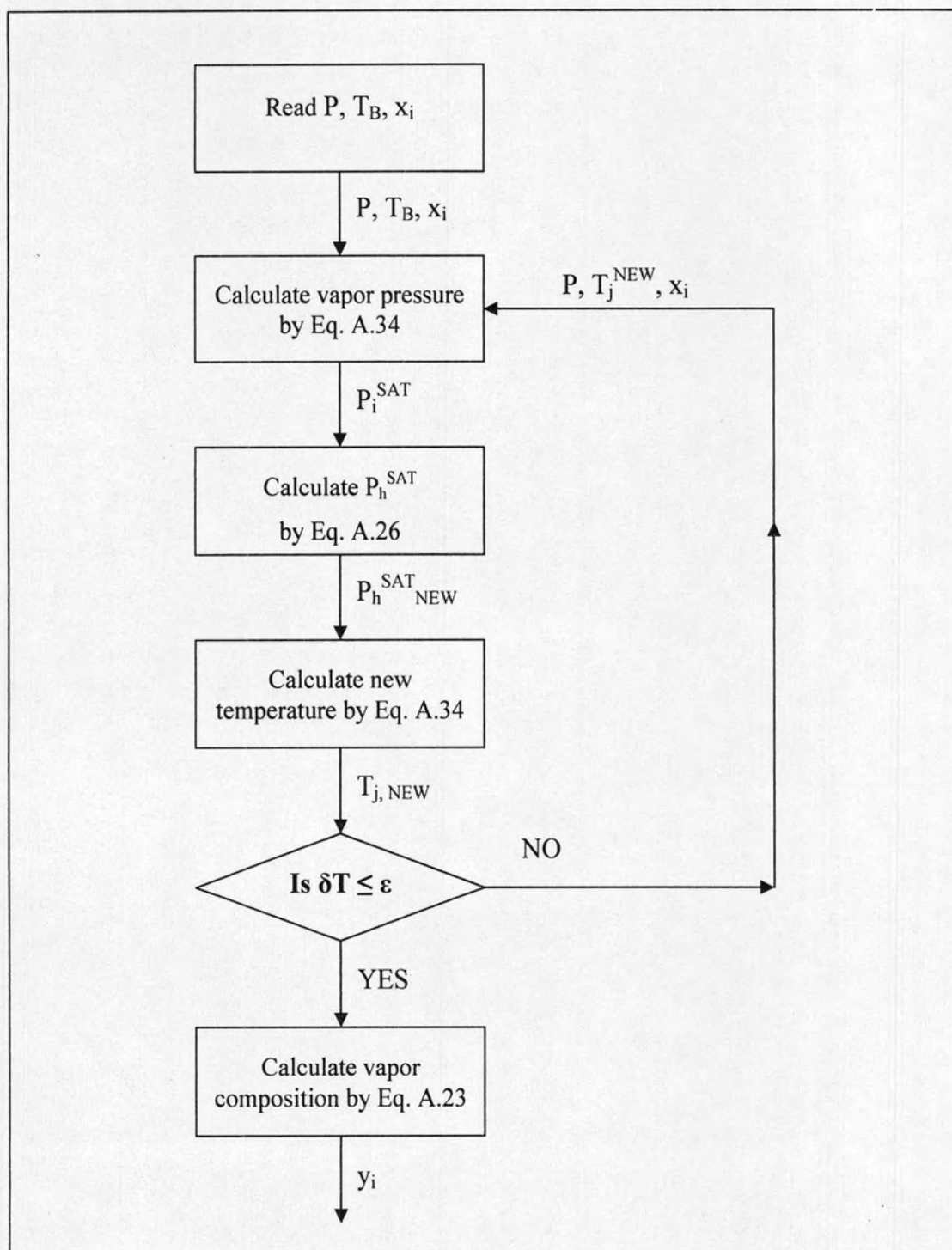


Figure A.6 Block diagrams for the calculation BUBL T

APPENDIX B

NEURAL NETWORK LEARNING ALGORITHM

This section described a BP training procedure which is based on gradient descent as the following.

B.1 Backpropagation Networks

For multilayer networks the output of one layer becomes the input to the following layer. The equations that describe this operation are

$$\mathbf{a}^{m+1} = \mathbf{f}^{m+1}(\mathbf{W}^{m+1} \mathbf{a}^m + \mathbf{b}^{m+1}) \quad \text{for } m = 0, 2, \dots, M-1 \quad (\text{B.1})$$

where M is the number of layers in the network. The neurons in the first layer receive external inputs:

$$\mathbf{a}^0 = \mathbf{p} \quad (\text{B.2})$$

This provides the starting point for Equation (4.26). The outputs of the neurons in the last layer are considered the network outputs:

$$\mathbf{a} = \mathbf{a}^M \quad (\text{B.3})$$

- *Performance Index*

The BP algorithm for multilayer networks use the performance index: *mean square error*, as show following

$$\begin{aligned} F(\mathbf{x}) &= E[(t - a)^2] \\ &= E[(t - a)^T (t - a)] \end{aligned} \quad (\text{B.4})$$

where \mathbf{x} is the vector of network weights and biases, \mathbf{t} is the corresponding target output. The steepest descent algorithm for the approximate mean square error is

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \eta \frac{\partial \bar{F}}{\partial w_{i,j}^m} \quad (\text{B.5})$$

$$b_i^m(k+1) = b_i^m(k) - \eta \frac{\partial \bar{F}}{\partial b_i^m} \quad (\text{B.6})$$

where η is the learning rate.

- *Chain Rule*

From Equations (4.xx) and (4.xx), the error is an indirect function of weights in the hidden layers. Therefore, the chain rule used to determine the error gradient following

$$\frac{\partial \bar{F}}{\partial w_{i,j}^m} = \frac{\partial \bar{F}}{\partial \xi_i^m} \times \frac{\partial \xi_i^m}{\partial w_{i,j}^m} \quad (\text{B.7})$$

$$\frac{\partial \bar{F}}{\partial b_i^m} = \frac{\partial \bar{F}}{\partial \xi_i^m} \times \frac{\partial \xi_i^m}{\partial b_i^m} \quad (\text{B.8})$$

The second term in each of these equations can be easily computed, since the net input to layer m is an explicit function of the weights and bias in that layer:

$$\xi_i^m = \sum_{j=1}^{S(m-1)} w_{i,j}^m a_j^{m-1} + b_i^m \quad (\text{B.9})$$

Therefore

$$\frac{\partial \xi_i^m}{\partial w_{i,j}^m} = a_j^{m-1}, \quad \frac{\partial \xi_i^m}{\partial b_i^m} = 1 \quad (\text{B.10})$$

Define

$$s_i^m \equiv \frac{\partial \bar{F}}{\partial \xi_i^m} \quad (\text{B.11})$$

(the sensitivity of \bar{F} to changes in the i th element of the net input at layer m), then Equation (4.x) and (4,x) can be simplified to

$$\frac{\partial \bar{F}}{\partial w_{i,j}^m} = s_i^m a_j^{m-1} \quad (\text{B.12})$$

$$\frac{\partial \bar{F}}{\partial b_i^m} = s_i^m \quad (\text{B.13})$$

Thus, the approximate steepest descent algorithm is

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \eta s_i^m a_j^{m-1} \quad (\text{B.14})$$

$$b_i^m(k+1) = b_i^m(k) - \eta s_i^m \quad (\text{B.15})$$

- *Backpropagation the Sensitivities*

The sensitivities s_i^m need to be determined for each neuron, which requires an other application of the chain rule. This process describes a recurrence relationship in which the sensitivity at layer m is computed from the sensitivity at layer $m+1$.

To derive the recurrence relationship for the sensitivities, consider the i,j element of the network

$$\begin{aligned} \frac{\partial \xi_i^{m+1}}{\partial \xi_j^m} &= \frac{\partial \left(\sum_{i=1}^{S(m)} w_{i,j}^{m+1} a_i^m + b_j^{m+1} \right)}{\partial \xi_j^m} = w_{i,j}^{m+1} \frac{\partial a_j^m}{\partial \xi_j^m} \\ &= w_{i,j}^{m+1} \frac{\partial f^m(\xi_j^m)}{\partial \xi_j^m} = w_{i,j}^{m+1} \dot{f}^m(\xi_j^m) \end{aligned} \quad (\text{B.16})$$

where

$$\frac{\partial f^m(\xi_j^m)}{\partial \xi_j^m} = \dot{f}^m(\xi_j^m) \quad (\text{B.17})$$

Therefore the Jacobian matrix can be written

$$\frac{\partial \xi^{m+1}}{\partial \xi^m} = \mathbf{W}^{m+1} \mathbf{F}^m(\mathbf{n}^m) \quad (\text{B.18})$$

where

$$\mathbf{F}^m(\mathbf{n}^m) = \begin{bmatrix} f^m(n_1^m) & 0 & \dots & 0 \\ 0 & f^m(n_2^m) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & f^m(n_{S^m}^m) \end{bmatrix} \quad (\text{B.19})$$

The recurrence relation for the sensitivity by using the chain rule in matrix form

$$\begin{aligned} s_i^m &= \frac{\partial \bar{F}}{\partial \xi_i^m} \\ &= \left(\frac{\partial \xi^{m+1}}{\partial \xi_i^m} \right)^T \frac{\partial \bar{F}}{\partial \xi_i^{m+1}} \\ &= \mathbf{F}^m(\mathbf{n}^m) (\mathbf{W}^{m+1})^T \mathbf{s}^{m+1} \end{aligned} \quad (\text{B.20})$$

APPENDIX C

PHYSICAL PROPERTIES

Table C.1 Properties of pure species

Formula	Name	MW (g/mol)	T_C (K)	T_B (K)
C ₆ H ₁₂	Cyclohexane	84.161	553.54	353.87
C ₇ H ₈	Toluene	92.141	591.79	383.78
C ₇ H ₁₆	n-Heptane	49.730	540.26	371.58

Table C.2 Heat capacity of gas

$$C_{p,i} = A + BT + CT^2 + DT^3 + ET^4 \text{ (J/mol}\cdot\text{K)}$$

Formula	Name	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
C ₆ H ₁₂	Cyclohexane	13.783	2.0742e-1	5.3682e-4	-6.3012e-7	1.8988e-10
C ₇ H ₈	Toluene	-24.097	5.2187e-1	-2.9827e-8	6.1220e-8	1.2576e-12
C ₇ H ₁₆	n-Heptane	26.984	5.0387e-1	-4.4748e-5	-1.6835e-7	6.5183e-11

Table C.3 Enthalpy of formation

$$\Delta H^\circ = A + BT + CT^2 \text{ (kJ/mol)}$$

Formula	Name	<i>A</i>	<i>B</i>	<i>C</i>	ΔH°_{298}
C ₆ H ₁₂	Cyclohexane	-81.822	-1.6705e-1	9.2830e-5	-123.14
C ₇ H ₈	Toluene	74.320	-9.5998e-2	4.7011e-5	50.00
C ₇ H ₁₆	n-Heptane	-144.670	-1.7028e-1	84.057e-5	-187.78

Table C.4 Enthalpy of vaporization

$$\Delta HV_{298,i} = A \left(1 - \frac{T}{T_c} \right)^n \text{ (kJ/mol)}$$

Formula	Name	<i>A</i>	<i>n</i>
C ₆ H ₁₂	Cyclohexane	49.060	0.486
C ₇ H ₈	Toluene	50.139	0.383
C ₇ H ₁₆	n-Heptane	49.730	0.386

Table C.5 Vapor pressure

$$\log_{10} P = A + (B/T) + (C \log_{10} T) + DT + ET^2 \text{ (mmHg)}$$

Formula	Name	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
C ₆ H ₁₂	Cyclohexane	48.5529	-3.0874e3	-1.5521e1	7.3830e-3	6.3563e-12
C ₇ H ₈	Toluene	34.0775	-3.0379e3	-9.1635e0	1.0289e-11	2.7035e-6
C ₇ H ₁₆	n-Heptane	65.0257	-3.8188e3	-2.1684e1	1.0387e-2	1.0206e-14

VITA

Arbhawadee Deachalamai was born in Bangkok, Thailand, on December 11, 1980. In 1999, she attended Kasetsart University, Bangkok, Thailand where she received the degree of Bachelor of Engineering in Chemical Engineering in 2003. Then, she entered the Graduate School of Chulalongkorn University to pursue a Master of Engineering in Chemical Engineering and completed in 2006.