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Artificial Neural Network Control of a Multiple Effect Evaporators via Simulation

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Abstract. This research studies the dynamic model and control of multiple effect evaporators of tomato solutions by implementing three control strategies: PID, neural model reference, and neural model predictive controllers. The evaporator's control is crucial to maintain the product specifications at different operation conditions at minimum operating cost. The model reference control and model predictive control has been designed and evaluated. The simulation results showed that the neural predictive controller is more suitable, has lower overshoot, less offset value, and less integral absolute error.

Keywords. Multiple effect evaporators, Neural reference controller, PID controller, Neural predictive controller.

1. Introduction

The principle utilized in the evaporator is a high pressure and temperature of steam, which acts as the heat supplier that is fed into the evaporator. The heat from the steam will increase the temperature of the evaporator, and at a specific high temperature, water in the liquid will start to vaporize, and a more concentrated product will be produced from the evaporator. The evaporation process is used in various industries, such as pharmaceuticals, food, and beverages, chemicals, and more [1]. The modeling and simulation of the integrated operation of the evaporator processes pose a significant challenge for every industrial plant. The firm interactions, high nonlinear behavior, extended and extremely time delays are the reason for the complexity [2]. The evaporation system's control objectives are maintaining the product specifications, operation constraints, and cost considerations. The complexity and the large number of interactions make single loop PID control difficult and often suboptimal. The conventional control methods are unsatisfactory because feed specifications change suddenly; hence the tight control of temperature using conventional methods is not satisfactory. Thus, it requires applying advanced control methods [3]. Kam et al. [4] simulated the nonlinear controller of an industrial five-effect evaporator of an alumina refinery. The simulation results showed that the nonlinear controller provides good performance to the multi-loop PI controllers. Benne et al. [5] modeled the multiple effect evaporation of the sugar industry. They developed the model-based predictive controller by predictor neural network model of the plant. They illustrated a good performance of this new approach. Smith [6] applied the model predictive controller on the multipleeffect evaporator to solve multiple inputs and multiple output variables. This method is compared with the PID controller, and the results show that the performer of the MPC controller is better than the PID controller. Rangaiah et al. [7] applied nonlinear model predictive and PI controllers of an industrial



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four-stage evaporator. They showed that the nonlinear model predictive controller is better than PI controllers. Karimi and Jahanmiri [8] developed an inferential cascade controller of a three-effect falling-film evaporator in a milk factory. The results show that the inferential controller achieves suitable control action concerning disturbances. Farsi and Jahanmiri [9] proposed and tuned the three conventional loops cascade control of evaporator. The results showed that the proposed control algorithm could significantly improve regulatory and servo responses. Atuonwu et al. [10] simulated a PI controller in parallel with a neural network of an industrial-scale five-stage evaporator. They tested this method and compared performance with PI controller with setpoint tracking and disturbance rejection problems. Chai et al. [11] applied the optimal control of a practical alumina evaporation process, and the results obtained are highly satisfactory. Wang et al. [12] applied an MPC and observer to improve disturbance rejection in the multiple-effect falling-film evaporator. The simulation results prove that the proposed method gave robust disturbance rejection compared with the MPC method. Verma et al. [13] applied the cascade-PID control of the heptode-effect evaporator in the paper industry. They improved the dynamic performance of the heat exchanger system versus open-loop dynamic response. Pan and Ning [14] studied the dynamic mathematical model of the evaporation system in the sugar mill and established it by mechanism analysis. They applied the PID and nonlinear adaptive predictive control algorithm. The error between the model output and the actual output is small, which satisfied the control requirements. It shows that the model has a good predictive ability. The simulation results showed that the predictive control algorithm has better robustness and stability than the PID control algorithm. This study aims to apply the PID, neural network model reference, and neural network model predictive controllers of the multiple effect evaporators of tomato solutions.

2. Mathematical modeling of the evaporator

The evaporator includes mass and heat transfer. The solution was considered as a binary solution of water and tomato. The evaporator is modeling based on total mass and component balances together with an energy balance. The evaporator is simulated based on the model equations presented below: Total mass balance at unsteady state [15]:

$$\frac{dM}{dt} = m_{in} - m - m_{vap} \tag{1}$$

Soluble solids mass balance:

$$\frac{d(c_{s}(t)M)}{dt} = m_{in}c_{s,in}(t)$$
(2)

Equation (2) can be written as :

$$\frac{d(c_s(t) M)}{dt} = c_s(t) \frac{dM}{dt} + M \frac{dc_s(t)}{dt}$$
(3)

Substituting Equations (1) and (3) in Equation (2) gives:

$$M \frac{dc_{s}(t)}{dt} = c_{s,in}(t)m_{in} - c_{s}(t)(m_{in} - m_{vap})$$
(4)

Rearranging Equation (4):

$$M \frac{dc_s(t)}{dt} + c_s(t) (m_{in} - m_{vap}) = c_{s,in}(t) m_{in}$$
(5)

Dividing Equation (5) by $(m_{in} - m_{vap})$ gives:

$$\tau_1 \frac{\mathrm{d} c_{\mathrm{s}}(t)}{\mathrm{d} t} + c_{\mathrm{s}}(t) = k_1 c_{\mathrm{s,in}}(t) \tag{6}$$

Where; $\tau_1 = \frac{M}{(m_{in} - m_{vap})}$ and $k_1 = \frac{m_{in}}{(m_{in} - m_{vap})}$ Taking the Laplace transform of Equation (6):

$$\tau_1 s c_s(s) + c_s(s) = k_1 c_{s,in}(s)$$
(7)

INTCSET 2020

IOP Conf. Series: Materials Science and Engineering 1094 (2021) 012004 doi:10.1088/1757-899X/1094/1/012004

$$G(s) = \frac{c_s(s)}{c_{s,in}(s)} = \frac{k_1}{\tau_1 s + 1}$$
(8)

Total energy balance at the unsteady state

$$\frac{d(MH)}{dt} = m_{in}H_{in} - mH - m_{vap}H_{vap} + Q_{steam}$$
(9)

Where Q:_{steam} is the steam-generating in the power plant

$$Q_{st} = m_{st}(H_{st} - H_c)$$
⁽¹⁰⁾

and the enthalpy of product concentration

$$H = cp T$$
(11)

$$cp = 4.1868 + 2.261 c_{\rm S} \tag{12}$$

Substitute Equations (10, 11 and 12) in Equation (9) gives:

$$M \operatorname{cp} \frac{\mathrm{dT}}{\mathrm{dt}} + T(t) \left[m_{\mathrm{in}} \operatorname{cp} - m_{vap} \operatorname{cp} - 2.261 \operatorname{m} \left(c_{\mathrm{s}}(t) - c_{\mathrm{s,in}}(t) \right) \right]$$

= $m_{\mathrm{in}} \operatorname{cp}_{\mathrm{in}} T_{\mathrm{in}}(t) + m_{\mathrm{st}}(t) (H_{st} - H_{\mathrm{c}})$ (13)

Dividing Equation (13) by $\left[m_{in} cp - m_{vap} cp - 2.261m (c_s(t) - c_{s,in}(t))\right]$ gives:

$$\frac{Mcp}{m_{in} cp - m_{vap} cp - 2.261m (c_{s}(t) - c_{s,in}(t))} \frac{dT}{dt} + T(t)
= \frac{m_{in} cp_{in}}{m_{in} cp - m_{vap} cp - m B (c_{s}(t) - c_{s,in}(t))} T_{in}(t)
+ \frac{(H_{s} - H_{c})}{m_{in} cp - m_{vap} cp - 2.261m (c_{s}(t) - c_{s,in}(t))} m_{st}(t)$$
(14)

Let:

$$\tau_{2} = \frac{Mcp}{m_{in} cp - m_{vap} cp - 2.261m (c_{s}(t) - c_{s,in}(t))}$$

$$k_{2} = \frac{m_{in} cp_{in}}{m_{in} cp - m_{vap} cp - 2.261m (c_{s}(t) - c_{s,in}(t))}$$

$$k_{3} = \frac{(H_{s} - H_{c})}{m_{in} cp - m_{vap} cp - 2.261m (c_{s}(t) - c_{s,in}(t))}$$

$$\tau_{2} \frac{dT}{dt} + T(t) = k_{2}T_{in}(t) + k_{3}m_{st}(t)$$
(15)

Taking the Laplace transform of Equation (15):

$$T(s) = \frac{k_2}{\tau_2 s + 1} T_{in}(s) + \frac{k_3}{\tau_2 s + 1}(s) m_{st}$$
(16)

At steady-state of T_{in} then Equation (16) became:

$$G(s) = \frac{T(s)}{m_{st}(s)} = \frac{k_3}{\tau_2 s + 1}$$
(17)

3. Neural network controller

The neural networks have been used prosperity in the modeling and control of dynamic systems [16]. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons, while the others are the hidden layers. A multilayer perceptron can learn when presented with input and output pairs [16]. In this study, a multilayer feed-forward neural network was applied to the evaporator with four input neurons, nine

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output neurons from the hidden layer and one output neurons from the output layer and with the (Tan-Sigmoid transfer function) activation function in hidden output and the (Linear transfer function) activation function in network output, as shown in Figure 1. The update weights and biases by using backpropagation learning algorithm during training to improve the performance. The general rule used to update the weight can be written as:

$$\Delta W ij = -\eta \frac{\partial E}{\partial W ij} \tag{18}$$

The new weight can be updated as follow:

$$Wij(k) = Wij(k-1) + \Delta Wij(k)$$
⁽¹⁹⁾

$$Wij(k) = Wij(k-1) + \Delta Wij(k) + \alpha \,\Delta Wij(k-1)$$
(20)

The operating parameters for the tomato system are shown in Table 1. The controllers are shown in Figures 2 and 3.



Figure 1. The neural network structure for the evaporator.

Table 1. Operating parameters for the Tomato system [17].

No.	Parameter	Value
1	Total no of effects	4
2	Feed Flow rate, kg/hr	12,000
3	Tomato Inlet concentration, kgsolid/kgsolution	0.06
4	Tomato Outlet concentration, kgsolid/kgsolution	0.28
5	Steam Temperature, °C	135
6	Feed Temperature, °C	60
7	Heat capacity of liquid solutions ($c_n = 4.184 - 2$.	9337 c _c)



Figure 2. Model reference control system.

IOP Conf. Series: Materials Science and Engineering

1094 (2021) 012004 doi:10.1088/1757-899X/1094/1/012004



Figure 3. NN Model predictive control system.

4. Simulation works

The process consists of the forward feed four effect evaporator of Tomato juice, as shown in Figure 4. The volume of evaporator and flow rate are 795 m³ and 437 m³/s, respectively. The diameter, length, and the number of the heat exchanger tubes are 0.05 m, 6 m, and 107, respectively. The MATLAB / Simulink software is used to simulate the evaporator depending on the mathematical model.



Figure 4. Multiple effect evaporation equipment [15].

5. Result and discussion

5.1. Dynamics of evaporator

The dynamic behavior is studied using step changes in steam flow rate, flow rate, and temperature of feed and finding the evaporator's transfer function, which was regarded as a first-order system. Table 2 shows the parameters of this system at different disturbance variables. The third and fourth effect evaporator response reaches a new steady-state condition with more time delay than the first and second effects evaporator. The time constant decreases with increasing steam flow rate. The time constant of the third evaporator is larger than the first and second evaporator.

Disturbance Variable	Evaporator		Evaporator		Evaporator		Evaporator	
	No.1		No. 2		No. 3		No. 4	
	K _P	τ (hr.)	K _P	τ (hr.)	K _P	τ (hr.)	K _P	T (sec.)
Steam flow rate	14.41	1.51	14.79	1.96	15.44	2.43	42.	3.57
Feed flow rate	-2.25	1.33	-12.31	1.79	-16	2.35	-8.61	3.01
Feed Temperature	9.78	1.45	9.11	2.63	4	3.11	7.23	4.88

Table 2. The parameters of the evaporator system.

5.2. Control of evaporator

In this section, a discussion of simulation results of the closed-loop is presented. In the present work, the object to maintain the controlled variable, the evaporator's outlet temperature at the desired value using three control methods: PID feedback and neural network controllers. The PID and neural network controllers are tested using step-change in feed flow rate and temperature using Integral

absolute error (IAE) for PID, as shown in Table 3. It can be seen that the IAE value of the PID controller needed a long time to reach the steady-state.

$$IAE = \int_{0}^{\infty} |E(t)| dt = \sum |T_{set} - T_{measured}| \Delta t$$
(21)

The PID controller showed a large degraded performance, as displayed in Figures 5 and 6, and it can be seen that the temperature has severe non-linear dynamics that depended on evaporation systems. The responses of neural controllers are fast, give smoother, smaller IAE error values, and perform better than the PID controller when step change is introduced into the systems. The figures clear that the neural strategy transported the evaporator temperature to the setpoints by the gradual increase of the flow rate, which gives a smooth control response. This indicates that neural controllers give less offset and give better control performance.



Figure 5. Comparison between PID and neural network (reference and predictive) controllers in the first evaporator to a step-change in temperature of feed from 60 - 70 °C at set point =92°C for tomato system.



Figure 6. Comparison between PID, fuzzy logic (seven membership functions), and neural network (predictive) controllers in the first evaporator to a step-change in feed flow rate from 12000 - 13000 kg/hr at set point =92°C for tomato system.

IOP Conf. Series: Materials Science and Engineering 1094 (2021) 012004 doi:10.1088/1757-899X/1094/1/012004

Item	Variable of the step-	Value of	Evap. No.			Control Mathad	
No.	change	step-change	1	2	3	4	-Control Method
1	Feed flow rate	12000 - 13000	0.4943	2.0411	0.6512	0.6987	DID
2	Temp. of feed (C ^o)	60 - 70	1.5523	1.8648	0.6008	0.6374	FID
3	Feed flow rate (kg/hr)	12000 - 13000	0.1201	1.5989	0.5024	0.4222	Neural Network
4	Temp. of feed (C°)	60 - 70	1.1061	1.8036	0.4729	0.5761	controller Neural
							Network controller
5	Feed flow rate (kg/hr)	12000 - 13000	0.0945	1.1331	0.4714	0.1303	Predictive Neural
6	Temp. of feed (C ^o)	60 - 70	0.8345	0.9716	0.4158	0.2072	Network controller

Table 3. The integral absolute error (IAE) for the neural network method.

6. Conclusion

The system of the evaporator is considered as a first-order lag. The integral of the absolute value of the error is used to test the performance of control methods. The PID controller is oscillating, needs a long time to reach the steady-state, has a higher IAE value, and has a high overshoot and settling time. The response of neural predictive controllers gives less error value and reaching the setpoint value in less time with lower over-shoot and indicated that neural predictive were more robust and gave better performance due to the disturbances.

Nomenclature				
c _{s,in}	Inlet concentration of tomato, (kgsolid/kgsolution)			
C _s	Outlet concentration of tomato, (kgsolid/kgsolution)			
Н	Product enthalpy, (kJ/kg)			
H _C	Condensate enthalpy, (kJ/kg)			
H _{in}	Feed enthalpy, (kJ/kg)			
H _{st}	Steam enthalpy of steam, (kJ/kg)			
H _{vap}	Vapor Enthalpy, (kJ/kg)			
М	Mass holdup, (kg)			
m	Product flow rate, (kg/sec)			
m _{in}	Feed flow rate, (kg/sec)			
m_{st} , m_{c}	Steam and condensate flow rate, (kg/sec)			
m _{vap}	Vapor flow rate, (kg/sec)			
Q _{steam}	Heat of steam, (kJ/sec)			
Т	Temperature of product, (°C)			
T _{in}	Feed temperature, (^o C)			
W _{ij}	Connection weight			
Greek letters				
α	Momentum rate			
τ	Time constant, (sec)			
$ au_{\mathrm{D}}$	Derivative time constant, (sec)			
$ au_{\mathrm{I}}$	Integral time constant, (sec)			
η	Learning rate			

7. References

- [1] McCabe, W L, Smith, J C and Harriott, P 1993 *Unit Operations of Chemical Engineering* (New York: McGraw-hill) p 154
- [2] Ordouei, M H 2009 Computer Aided Simulation and Process Design of a Hydrogenation Plant Using Aspen HYSYS 2006 (MSc. Thesis, University of Waterloo) pp 1–3
- [3] Seborg, D E, F Edgar, T and Mellichamp, D A 2004 *Process Dynamics and Control* (John Wily & sons, USA)
- [4] Kam, K M and Tadé, M O 2000 Simulated Nonlinear Control Studies of Five-Effect Evaporator Models (Computers & Chemical Engineering) vol 23 pp 1795–1810
- [5] Benne, M, Grondin-Perez, B, Chabriat, J P and Herve, P 2000 Artificial Neural Networks for Modelling and Predictive Control of an Industrial Evaporation Process (Journal of Food Engineering) vol 46 no 4 pp 227–234

IOP Conf. Series: Materials Science and Engineering 1094 (2021) 012004 doi:10.1088/1757-899X/1094/1/012004

- [6] Smith, P D 2000 Control and Optimization of A Multiple-Effect Evaporator (Doctoral dissertation, University of Cape Town)
- [7] Rangaiah, G P, Saha, P and Tadé, M O 2002 Nonlinear Model Predictive Control of An Industrial Four-Stage Evaporator System Via Simulation (Chemical Engineering Journal) vol 87 no 3 pp 285–299
- [8] Karimi, M and Jahanmiri, A 2006 *Nonlinear Modeling and Cascade Control Design for Multi Effect Falling Film Evaporator* (Iranian Journal of Chemical Engineering) vol 3 no 2
- [9] Farsi, M and Jahanmiri, A 2009 A New Control Algorithm for Concentration Control in Three Effect Falling Film Evaporators (Iranian Journal of Science & Technology, Transection B, Engineering) vol 33 no B5, pp 387–396
- [10] Atuonwu, J, C, Cao, Y, Rangaiah, G, P and Tade, M, O 2010 *Identification and Predictive Control of Multistage Evaporator* (Control Engineering Practice) vol 18 pp 1418–1428
- [11] Chai, Q, Q, Yang, C, H, Teo, K, L and Gui, W, H 2012 Optimal Control of an Industrial Scale Evaporation Process : Sodium Aluminate Solution (Control Engineering Practice) vol 20 pp 618–628
- [12] Wang, X, Li, C and Chen, X 2016 Disturbance Rejection Control for Multiple-Effect Falling-Film Evaporator Based on Disturbance Observer (Transactions of the Institute of Measurement and Control) vol 38 no 6 pp 773–783
- [13] Verma, O P, Manik, G and Mohammed, T H 2017 Energy Management In Multi Stage Evaporator Through A Steady And Dynamic State Analysis (Korean Journal of Chemical Engineering) vol 34 no 10 pp 2570–2583
- [14] Pan, D and Ning, C 2019 Mechanism Modeling and Nonlinear Model Adaptive-Predictive Control of Multiple Evaporators System in Sugar Mill (International Conference on Intelligent Transportation, IEEE, Big Data & Smart City) pp 528–532
- [15] Zainab A Khalaf 2014 Simulation on Dynamic and Control of Evaporator Using MATLAB (M Sc. Thesis, Tikrit University) pp 23–30
- [16] Ahmed, D F 2014 Artificial Neural Network Control of Chemical Processes (Eng. & Tech. Journal) vol 32 Part A no 1 pp 176–196
- [17] Miranda, V, Simpson, R 2004 Modeling and Simulation of an Industrial Multiple Effect Evaporator : Tomato Concentrate (Journal of food Engineering) vol 66 pp 203–210

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