Nonlinear Model Predictive Control of a Distillation Column Using Wavenet Based Hammerstein Model

K. Ramesh, A. Hisyam, N. Aziz and S.R. Abd Shukor

Abstract - **Distillation columns are fairly complex multivariable systems and needs to be controlled close to optimum operating conditions because of economic incentives. Nonlinear Model Predictive Control (NMPC) scheme is one of the best options to be explored for proper control of distillation columns. In the present work, a new wavenet based Hammerstein model NMPC has been developed to control distillation column. An experimentally validated equilibrium model was used as plant model in nonlinear system identification and in NMPC. Two multiple-input-single-output (MISO) wavenet based Hammerstein models are developed to model the dynamics of the distillation column. The nonlinear model parameters were estimated using iterative prediction-error minimization method. The Unscented Kalman Filter (UKF) was used to estimate the state variables in NMPC and the NLP problem was solved using sequential quadratic programming (SQP) method. The closed loop control studies have indicated that the performance of developed NMPC scheme was good in controlling the distillation column.**

Key words - Distillation column; Nonlinear model predictive control; Sequential quadratic programming; Wavenet based Hammerstein model.

I. INTRODUCTION

Distillation columns are important processing units in petroleum refineries and other chemical processing industries (CPI) for separating feed streams, and for purification of final and intermediate product streams [1]. The separation needs relatively large amount of energy. Close control of distillation column improves the product quality, minimizes energy usage and maximizes the plant throughput and its economy [2]. Most of the industrial distillation columns are currently controlled by multiloop controllers based on linear models. Among the multivariable controllers, Model Predictive Control (MPC) is an important advanced control technique which can be used for difficult multivariable control problems [3]. MPC refers to the class of control algorithms in which dynamic process model is used to predict and optimize the process performance. The current generation of commercially available MPC technology is based on linear dynamic models, and is refereed by the general term linear model predictive control (LMPC). Many processes such as high purity distillation column, multi-grade polymer reactors are sufficiently nonlinear to preclude the successful application of LMPC technology [4]. This has led to the development of nonlinear model based controllers such as nonlinear model predictive control (NMPC) in which more accurate nonlinear model is used for process prediction and optimization.

Many authors have studied the performance of NMPC to control distillation column using different nonlinear models namely semi-rigorous reduced order model [5], NARX model [6], Hammerstein model [7], Recurrent Dynamic Neuron Network (RDNN) model [8] and grouped neural networks (GNN) model [9]. Foss *et al.* [10] in their case study on process modeling in Germany and Norway concluded that despite the commercially available modeling tools, the effort spent for all kinds of modeling activities is the most time consuming step in an industrial project where model based process engineering techniques are applied.

The NMPC problem formulation involves online computation of a sequence of manipulated inputs which optimize an objective function and satisfy process constraints. The development of NMPC techniques for large scale systems may require problem formulations which exploit the specific structure of the nonlinear model. Finally, NMPC requires online solution of a nonlinear program (NLP) at each iteration. The solution of such NLP problems can be very time consuming, especially for large scale systems. An additional complication is that the optimization problem generally is nonconvex because the nonlinear model equations are posed as constraints [11]. Consequently, NLP solvers designed for convex problems may converge to local minima or even diverge. So it is necessary to find out an improved solution algorithm for nonconvex NLP problems.

The vital parts of the present study are to develop suitable nonlinear model for distillation column, formulate NMPC problem and to find out an efficient optimization algorithm to be used with NMPC. Two multiple-input-single-output

Manuscript received June 12, 2012, revised July 17, 2012.

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(MISO) wavenet based Hammerstein models are developed in this study to model the dynamics of the distillation column. An experimentally validated equilibrium model was used as plant model in nonlinear system identification and in NMPC. The remainder of the paper is organized as follows. Section Two provides the nonlinear system identification of new wavenet based Hammerstein model. The NMPC problem formulation, state estimation and optimization algorithm are explained in Section Three and the results of closed loop control studies are presented in Section Four. Finally concluding remarks are mentioned in Section Five.

II. WAVENET BASED HAMMERSTEIN MODEL

The details of pilot plant distillation column used in this study and the experimental validation of equilibrium model were discussed in [12]. The Hammerstein model consists of a nonlinear static element followed in series by a linear dynamic element. In this study, two separately parameterized nonlinearity structured multiple-input-single-output (MISO) wavenet based Hammerstein models are developed to model the dynamics of the distillation column. The reason for using two MISO models instead multiple-input-multiple-output (MIMO) model is that the MISO models provide better prediction compared to MIMO model [13] The first MISO model using reflux flow rate (L) and reboiler heat load (Q_R) as inputs, and top product composition (x_D) as output, while, the second MISO model using reflux flow rate (L) and reboiler heat load (Q_R) as inputs, and bottom product composition (x_B) as output. In both the MISO Hammerstein models a new wavenet based nonlinear function is used to describe the nonlinear static block and Output Error (OE) model is used to describe the linear dynamic block.

The linear block is the Output Error (OE) model, given by the following equation.

$$y(k)=\frac{B_1(q^{-1})}{A_1(q^{-1})}x_1(k)+\frac{B_2(q^{-1})}{A_2(q^{-1})}x_2(k) \tag{1}$$

The polynomials $B_1(q^{-1}), A_1(q^{-1}), B_2(q^{-1})$ and $A_2(q^{-1})$ in Equation (1) are defined as

$$B_1(q^{-1})=b_{11}q^{-nk}+b_{21}q^{-(nk+1)}+...+b_{nb1}q^{-(nk+nb+1)} \tag{2}$$

$$A_1(q^{-1})=1+a_{11}q^{-1}+a_{21}q^{-2}+...+a_{na1}q^{-na} \tag{3}$$

$$B_2(q^{-1})=b_{12}q^{-nk}+b_{22}q^{-(nk+1)}+...+b_{nb2}q^{-(nk+nb+1)} \tag{4}$$

$$A_2(q^{-1})=1+a_{12}q^{-1}+a_{22}q^{-2}+...+a_{na2}q^{-na} \tag{5}$$

where,
nb is the number of coefficients in $B_1(q^{-1})$ and $B_2(q^{-1})$
na is the number of coefficients in $A_1(q^{-1})$ and $A_2(q^{-1})$
nk is the delay from input to output
$b_{11}, b_{21}, \ldots, b_{nb1}$ are the coefficients of polynomial B_1
$a_{11}, a_{21}, \ldots, a_{na1}$ are the coefficients of polynomial A_1
$b_{12}, b_{22}, \ldots, b_{nb2}$ are the coefficients of polynomial B_2
$a_{12}, a_{22}, \ldots, a_{na2}$ are the coefficients of polynomial A_2

Wavenet structure based nonlinear function $x = F(u)$ is used to represent the static nonlinearity of the Hammerstein model.

$$\begin{aligned}x_1(k)=F(u_1)&=(u_1-r_1)P_1L_1+as_{11}f(bs_{11}((u_1-r_1)Q_1cs_{11}))\\&+...+as_{k1}f(bs_{k1}((u_1-r_1)Q_1cs_{k1}))+aw_{11}g(bw_{11}((u_1-r_1)Q_1-cw_{11}))\\&+...+aw_{k1}g(bw_{k1}((u_1-r_1)Q_1-cw_{k1}))+d_1\end{aligned} \tag{6}$$

$$\begin{aligned}x_2(k)=F(u_2)&=(u_2-r_2)P_2L_2+as_{12}f(bs_{12}((u_2-r_2)Q_2cs_{12}))\\&+...+as_{k2}f(bs_{k2}((u_2-r_2)Q_2cs_{k2}))+aw_{12}g(bw_{12}((u_2-r_2)Q_2-cw_{12}))\\&+...+aw_{k2}g(bw_{k2}((u_2-r_2)Q_2-cw_{k2}))+d_2\end{aligned} \tag{7}$$

Substituting Equations (6) and (7) in Equation (1), the output of the wavenet based Hammerstein model $y(k)$ is given by

$$\begin{aligned}y(k)=&\frac{B_1(q^{-1})}{A_1(q^{-1})}(u_1-r_1)P_1L_1+as_{11}f(bs_{11}((u_1-r_1)Q_1cs_{11}))\\&+...+as_{k1}f(bs_{k1}((u_1-r_1)Q_1cs_{k1}))+aw_{11}g(bw_{11}((u_1-r_1)Q_1-cw_{11}))\\&+...+aw_{k1}g(bw_{k1}((u_1-r_1)Q_1-cw_{k1}))+d_1\\&+\frac{B_2(q^{-1})}{A_2(q^{-1})}(u_2-r_2)P_2L_2+as_{12}f(bs_{12}((u_2-r_2)Q_2cs_{12}))\\&+...+as_{k2}f(bs_{k2}((u_2-r_2)Q_2cs_{k2}))+aw_{12}g(bw_{12}((u_2-r_2)Q_2-cw_{12}))\\&+...+aw_{k2}g(bw_{k2}((u_2-r_2)Q_2-cw_{k2}))+d_2\end{aligned} \tag{8}$$

The scaling functions $f(u_1)$ and $f(u_2)$ in Equation (6) & (7) are given by

$$f(u_1)=\exp(-0.5u_1'u_1) \tag{9}$$

$$f(u_2)=\exp(-0.5u_2'u_2) \tag{10}$$

The wavelet functions $g(u_1)$ and $g(u_2)$ in Equation (6) & (7) are given by

$$g(u_1)=(\dim(u_1)-u_1'u_1)\exp(-0.5u_1'u_1) \tag{11}$$

$$g(u_2)=(\dim(u_2)-u_2'u_2)\exp(-0.5u_2'u_2) \tag{12}$$

where,
P_1 and P_2 are nonlinear subspace parameters
Q_1 and Q_2 are linear subspace parameters
r_1 and r_2 are regressor means
L_1 and L_2 are linear term coefficients in wavenet function
aw_{k1} and aw_{k2} are wavelet coefficients
bw_{k1} and bw_{k2} are wavelet dilation coefficients
cw_{k1} and cw_{k2} are wavelet translation coefficients
as_{k1} and as_{k2} are scaling coefficients
bs_{k1} and bs_{k2} are scaling dilation coefficients
cs_{k1} and cs_{k2} are scaling translation coefficients
d_1 and d_2 are output offsets

The experimentally validated equilibrium model was used as plant model to generate data required for nonlinear model identification. The system identification toolbox version 7.0 in MATLAB was employed for parameter estimation. The model parameters were estimated using iterative prediction-error minimization method. Random Gaussian input sequence is used to make changes in reflux flow rate (L) and

TABLE I
PARAMETERS OF MISO HAMMERSTEIN MODELS

Model parameters	First MISO model	Second MISO model
Linear OE model Parameters	a_{11} = -1.334, a_{21} = 0.36 a_{12} = -1.316, a_{22} = 0.3406 b_{11} = 1, b_{12} = 1	a_{11} = -1.338, a_{21} = 0.3498 a_{12} = -1.092, a_{22} = 0.109 b_{11} = 1, b_{12} = 1
Nonlinear subspace Parameters	P_1 = 55.13 P_2 = 2.991	P_1 = 55.13 P_2 = 2.984
Linear subspace parameters	Q_1 = 55.13 Q_2 = 2.991	Q_1 = 55.13 Q_2 = 2.984
Linear term coefficients in wavenet function	$L_1 = 1.385 \times 10^{-4}$ $L_2 = -1.438 \times 10^{-4}$	$L_1 = 2.804 \times 10^{-4}$ $L_2 = -5.015 \times 10^{-4}$
Output offsets	$d_1 = -2.61 \times 10^{-4}$ $d_2 = 2.45 \times 10^{-4}$	$d_1 = -5.21 \times 10^{-4}$ $d_2 = 7.37 \times 10^{-4}$
Regressor means	$r_1 = 4.02 \times 10^{-4}$ r_2 = -0.0046	$r_1 = 4.13 \times 10^{-4}$ r_2 = -0.0044
Wavelet coefficients	$aw_{11} = -0.017 \times 10^{-4}$ $aw_{12} = -0.209 \times 10^{-4}$	$aw_{11} = -9.45 \times 10^{-6}$ $aw_{12} = -7.48 \times 10^{-5}$
Wavelet dilation coefficients	bw_{11} = 15.99 bw_{12} = 15.803	bw_{11} = 15.53 bw_{12} = 15.98
Wavelet translation coefficients	cw_{11} = -2.024 cw_{12} = 1	cw_{11} = -0.5621 cw_{12} = 1
Scaling coefficients	as_{11} = 0 $as_{12} = -1.75 \times 10^{-5}$	$as_{11} = -4.33 \times 10^{-5}$ $as_{12} = 6.04 \times 10^{-5}$
Scaling dilation coefficients	bs_{11} = 0.005 bs_{12} = 16.01	bs_{11} = 31.104 bs_{12} = 16.002
Scaling translation coefficients	cs_{11} = -0.014 cs_{12} = 1	cs_{11} = 0.8469 cs_{12} = 1

reboiler heat load (Q_B) simultaneously, in order to generate data used for nonlinear model identification. The model parameters are given in Table I. The first and second MISO Hammerstein models showed 94.64% and 95.12% agreement with the equilibrium model respectively.

III. NMPC

The developed nonlinear wavenet based Hammerstein model is of the following form.

$$X(k+1) = F[X(k), U(k)] \tag{13}$$

$$Y(k) = h[X(k)] \quad (14) \tag{14}$$

where

$$X(k) = [x_1(k)\ x_2(k)]^T$$

$$U(k) = [u_1(k)\ u_2(k)]^T$$

$$Y(k) = [y_1(k)\ y_2(k)]^T$$

x_1 and x_2 are n-dimensional vector of state variables, u_1 (reflux flow rate) and u_2 (reboiler heat load) are m-dimensional vectors of manipulated input variables, and y_1 (top product composition) and y_2 (bottom product composition) are p-dimensional vector of controlled output variables. In this work, two separate MISO models were developed (one for each output) instead of using a MIMO model.

The optimization problem is given by

$$\min_{U(k\backslash k), U(k+1\backslash k) \ldots, U(k+M-1\backslash k)} J = \phi[\mathbf{Y}(k+P\backslash k)] + \sum_{j=0}^{P-1} L\left[Y(k+j\backslash k, U(k+j\backslash k), \Delta U(k+j\backslash k)\right] \tag{15}$$

where $U(k + j\backslash k)$ is the input $U(k + j)$ calculated from information available at time k, $Y(k + j\backslash k)$ is the output $Y(k + j)$ calculated from information available at time k, $\Delta U(k + j\backslash k) = U(k + j\text{-}1\backslash k) - U(k + j\backslash k)$, M is the control horizon, P is the prediction horizon and φ and L are nonlinear functions of their arguments. The functions φ and L can be chosen to satisfy wide variety of objectives and in this study, the quadratic functions of the following form is considered:

$$\begin{aligned} L = {} & [Y(k+j\backslash k - Y_s(k)]^T Q[Y(k+j\backslash k - Y_s(k)] \\ & + [U(k+j\backslash k - U_s(k)]^T R[U(k+j\backslash k - U_s(k)] \\ & + \Delta U^T(k+j\backslash k) S \Delta U(k+j\backslash k) \end{aligned} \tag{16}$$

$$\phi = [Y(k+P\backslash k) - Y_s(k)]^T Q[Y(k+P\backslash k) - Y_s(k)] \tag{17}$$

where $U_s(k)$ and $Y_s(k)$ are steady-state targets for U and Y respectively, and Q, R and S are positive-definite weighing matrices. The principal controller tuning parameters are M, P, Q, R, S and the sampling period Δt.

An important characteristic of process control problems is the presence of constraints on input and output variables. A major advantage of NMPC, compared to other nonlinear control strategies is that it provides explicit constraint handling capacity. In distillation control using NMPC, input constraints take the following form:

$$u_{1\min} \le u_1 \le u_{1\max} \quad (18a)$$

$$u_{2\min} \le u_2 \le u_{2\max} \quad (18b)$$

$$\Delta u_{1\min} \le \Delta u_1 \le \Delta u_{1\max} \quad (18c)$$

$$\Delta u_{2\min} \le \Delta u_2 \le \Delta u_{2\max} \quad (18d)$$

where,
$u_{1\min}$ - Minimum value of the reflux flow rate
$u_{1\max}$ - Maximum value of the reflux flow rate
$u_{2\min}$ - Minimum value of the reboiler heat load
$u_{2\max}$ - Maximum value of the reboiler heat load
$\Delta u_{1\min}$ - Minimum value of rate of change of reflux flow rate
$\Delta u_{1\max}$ - Maximum value of rate of change of reflux flow rate
$\Delta u_{2\min}$ - Minimum value of rate of change of reboiler heat load
$\Delta u_{2\max}$ - Maximum value of rate of change of reboiler heat load

The reflux flow rate bounds are set to be [0.1, 0.75] l/min. The lower bound for reflux flow rate 0.1 l/min was meant to keep the input physically meaningful, namely, the reflux flow rate should be positive and have some minimum value. The upper bound of reflux flow rate is approximately 150% of the nominal capacity, which would seldom occur in operation. The reboiler heat load bounds are set to be [0, 15] kW. The lower bound meant that the reboiler heat load should not be negative, whereas upper bound 15 kW was the maximum heater capacity of the reboiler.

Output constraints usually are associated with operational limitations such as equipment specifications and safety considerations. The output constraint can be posed as

$$y_{1\min} \le y_1 \le y_{1\max} \quad (19a)$$

$$y_{2\min} \le y_2 \le y_{2\max} \quad (19b)$$

where
$y_{1\min}$ - Minimum value of the top product composition
$y_{1\max}$ - Maximum value of the top product composition
$y_{2\min}$ - Minimum value of the bottom product composition
$y_{2\max}$ - Maximum value of the bottom product composition

The top product composition bounds are set to be [0.5, 1]. The lower bound for output 0.5 was meant that the top product purity should not be less than 50%. The upper bound 1 was meant that the maximum value of top product purity is 100% and beyond that is practically not meaningful. The bottom product composition bounds are set to be [0, 0.5]. The lower bound for bottom product composition 0 was meant that the maximum value of bottom product purity is 100%. The upper bound of bottom product composition 0.5 was meant that the bottom product purity should not be less than 50%. A major advantage of NMPC compared to other nonlinear control strategies is that it provides the constraint handling capability. The desired product purity is achieved by solving the nonlinear optimization problem subject to the following inequality constraints.

$$U_{\min} \le U(k+j\backslash k) \le U_{\max}, \quad 0 \le j \le M-1 \quad (20a)$$

$$\Delta U_{\min} \le \Delta U(k+j\backslash k) \le \Delta U_{\max}, \quad 0 \le j \le M-1 \quad (20b)$$

$$Y_{\min} \le Y(k+j\backslash k) \le Y_{\max}, \quad 1 \le j \le P \quad (20c)$$

In addition, the nonlinear model equations are posed as a set of following equality constraints:

$$X(k+j+1\backslash k) = F[X(k+j\backslash k), U(k+j\backslash k)], \quad 0 \le j \le P-1 \quad (21)$$

$$Y(k+j\backslash k) = h[X(k+j\backslash k)], \quad 1 \le j \le P \quad (22)$$

where $X(k\backslash k) = X(k)$ if the state variables are measured. It is important to note that input constraints are hard constraints in the sense that they must be satisfied. Conversely, output constraints can be viewed as soft constraints because their violation is necessary to obtain a feasible optimization problem.

NMPC calculation requires measurements or estimates of the state variables and in the present work, UKF was used to estimate the state variables in the NMPC problem. In UKF, the state distribution is represented by a Gaussian Random Variables (GRV), which is specified using a minimal set of carefully chosen sample points. These sample points completely capture the true mean and covariance of the GRV, and when propagated through the true non-linear system, captures the posterior mean and covariance accurately to the third order of Taylor series expansion for any nonlinearity [14]. Finally, the NMPC problem was solved using *fmincon* function in MATLAB optimization toolbox version 3.1.1which uses a sequential quadratic programming (SQP) method.

IV. CLOSED LOOP CONTROL STUDIES

Closed loop control studies were carried out to verify the performance of wavenet based Hammerstein model NMPC. These studies include disturbance rejection of NMPC for feed flow rate and feed composition changes, and set point tracking of NMPC for changes in set points of top and bottom product compositions. The closed loop simulation studies were done through MATLAB version 7.4.0.287 (R2007a). A sampling interval of 1 min was chosen for closed loop control studies. The NMPC parameters M, P, Q, R, S and the sampling period Δt are chosen by repeated tuning and the final values are; sampling period Δt = 1 min, prediction horizon P = 30 time steps (30 min), control horizon M = 6 time steps (6 min), Q = (1,0.5), R = (1,1) and S = (1,1). The experimentally validated equilibrium model for distillation column was used as plant model in closed loop control studies.

The performance of the NMPC was studied by making three feed flow rate disturbances: a +20% increase at t = 0 min, again a +20% increase at t = 40 min and a -20% decrease at t = 80 min. The responses of product compositions for these feed flow rate disturbances are shown in Figure 1 and it can be seen from the Figure 1 that the Hammerstein NMPC successfully rejected the feed flow rate disturbances within 20 min. The integral of absolute value of error (IAE) was calculated for each output and the numerical values of IAE performance index were indicated in all the NMPC responses of product compositions. The corresponding responses of manipulated variables to feed flow rate disturbances are shown in Figure 2.

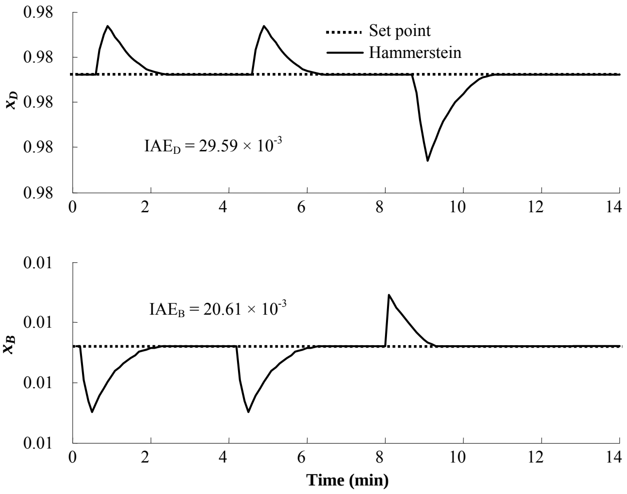

Fig. 1. Hammerstein NMPC responses of product compositions to a feed flow rate disturbance

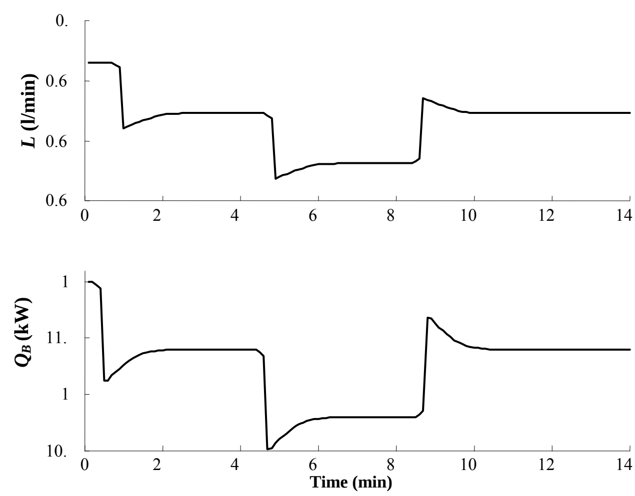

Fig. 2. Hammerstein NMPC responses of manipulated variables to a feed flow rate disturbance

The performance of the NMPC in set point tracking was studied by making -3% change in x_D at t = 10 min followed by -3% change in x_B at t = 50 min. The responses of product compositions for these set point changes are shown in Figure 3 along with the corresponding numerical values of IAE performance index. It can be seen from the Figure 3 that the Hammerstein NMPC successfully tracking the set-point quickly. The corresponding responses of manipulated variables for set point changes are shown in Figure 4.

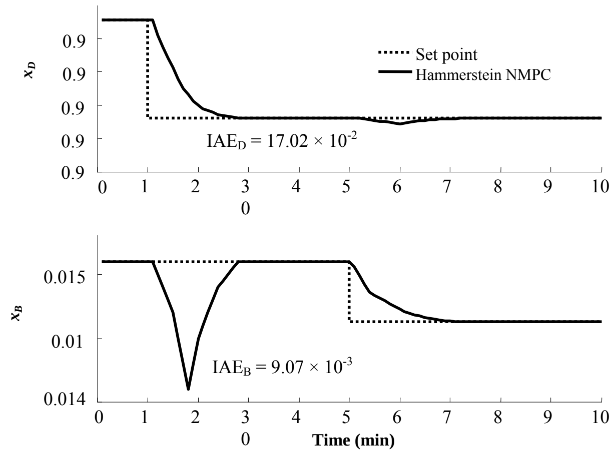

Fig. 3. Hammerstein NMPC responses of product compositions to -3% change in x_D at t =10 min and -3% change in x_B at t = 50 min

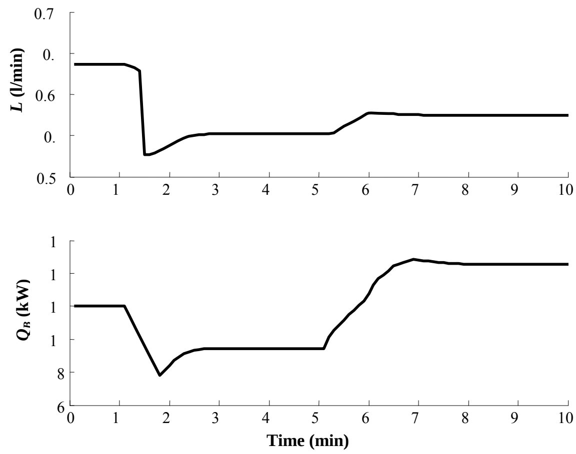

Fig. 4. Hammerstein NMPC responses of manipulated variables to -3% change in x_D at t =10 min and -3% change in x_B at t = 50 min

The control performance of the Hammerstein NMPC for simultaneous changes in both set points and load variables was studied by making following changes: a -3% change in x_D along with a +20% change in feed flow rate at t = 10 min and a -3% change in x_B along with a -10% change in feed composition at t = 50 min. The responses of product compositions for these changes along with their actual set points are shown in Figure 5 and the corresponding responses of manipulated variables are shown in Figure 6. It was noted that the changes in Q_B is close to the upper limit of the reboiler heat load. The IAE performance of index for top and bottom product compositions was found to be 18×10^{-2} and 24.47×10^{-3} respectively.

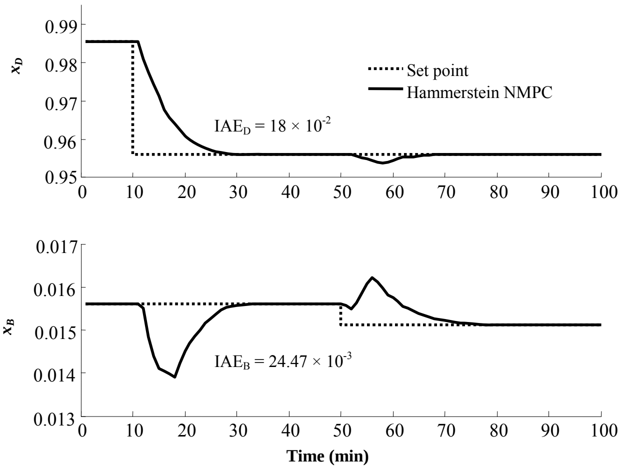

Fig. 5. Hammerstein NMPC responses of product compositions for simultaneous changes in set points and disturbances

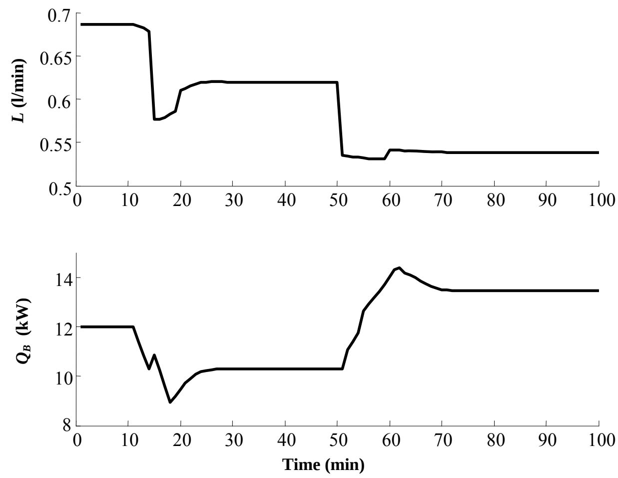

Fig. 6. Hammerstein NMPC responses of manipulated variables for simultaneous changes in set points and disturbances

V. CONCLUSION

Two wavenet based MISO Hammerstein models were developed to be used with NMPC to control distillation column. An experimentally validated equilibrium model was used as plant model in nonlinear system identification and in NMPC. The model parameters were estimated using iterative prediction-error minimization method. The Unscented Kalman Filter (UKF) was used to estimate the state variables in NMPC and the NLP problem was solved using sequential quadratic programming (SQP) method. The closed loop control studies indicated that the developed NMPC technique performed well in controlling the distillation column by rejecting the disturbances in regulatory control and tracking the set points quickly in servo control. .

REFERENCES

[1] J.J. Downs and J.E. Doss. "Present status and future needs-A view from North American industry". in *Proceeedings of the international conference on chemical process control* 1991. Padre Island, TX, USA.

[2] S. Hurowitz, et al., "Distillation control configuration selection". *Journal of Process Control*, 2003. **13**(4): pp. 357-362.

[3] G.C. Goodwin, S.F. Graebe and M.E. Salgado, *Control System Design*. 2001, Upper Saddle River, NJ: Prentice Hall.

[4] M.A. Henson, "Nonlinear model predictive control: Current status and future directions". *Computers and Chemical Engineering*, 1998. **23**(2): pp. 187-202.

[5] S.N. Maiti, S. Ganguly and D.N. Saraf, "Some new approaches for the control of a distillation column and their experimental evaluation on a pilot plant". *Computers & Chemical Engineering*, 1995. **19**(Supplement 1): pp. 399-404.

[6] G.R. Sriniwas, et al., "Nonlinear identification and control of a high-purity distillation column: a case study". *Journal of Process Control*, 1995. **5**: pp. 149-162.

[7] K.P. Fruzzetti, A. Palazoglu and K.A. McDonald, "Nonlinear model predictive control using Hammerstein models". *Journal of Process Control*, 1997. **7**(1): pp. 31-41.

[8] A.M. Shaw and F.J. Doyle III, "Multivariable nonlinear control applications for a high purity distillation column using a recurrent dynamic neuron model ". *Journal of Process Control*, 1997. **7**(4): pp. 255-268.

[9] J. Ou and R.R. Rhinehart, "Grouped neural network model-predictive control". *Control Engineering Practice*, 2003. **11**(7): pp. 723-732.

[10] F. Michelsen and B. Foss, "A comprehensive mechanistic model of a continuous Kamyr digester". *Applied Mathematical Modeling*, 1996. **20**: pp. 523-533.

[11] M. Cannon, "Efficient nonlinear model predictive control algorithms". *Annual Reviews in Control*, 2004. **28**: pp. 229-237.

[12] K. Ramesh, N. Aziz and S.R. Abd Shukor, "Nonlinear model predictive control of a distillation column using NARX model". *Computer Aided Chemical Engineering*, 2009. **27**: pp. 1575-1580.

[13] E. Eskinat, S.H. Johnson and W.L. Luyben, " Use of Hammerstein models in identification of nonlinear systems". *A.I.Ch.E. Journal*, 1991. **37**(2): pp. 255–268.

[14] E.A. Wan and R.V.D. Merwe. "The Unscented Kalman Filter for Nonlinear Estimation". in *In Proceedings of Symposium 2000 on Adaptive Systems for Signal Processing, Communication and Control (AS-SPCC)*. 2000. Lake Louise, Alberta, Canada.: IEEE.