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PROCESS MODELING AND CONTROL OF NONLINEAR pH PROCESS USING HAMMERSTEINWIENERMODEL AND MODEL PREDICTIVE CONTROL

M.Nandhini[1]

M.Florance Mary[2]

R.Ananda Natarajan[3]

Abstract

Efficient Hammerstein Wiener model can be determined by considering fitness of the model, loss function value and final prediction error. Using these data the model which best fits the process can be determined. A model based controller that uses Hammerstein Wiener model as the internal model for a nonlinear MPC as Hammerstein based Model Predictive Controller (HMPC) is used in controlling pH neutralization process. The simulation results show that Hammerstein based Model Predictive Controller (HMPC) outperforms linear Model Predictive Controller (MPC) for control of pH process.

Keywords:

Hammerstein Wiener model;
Model Predictive Controller;
pH neutralization process;

Author correspondence:

M.Florance Mary,

Dept. of Electronics and Instrumentation Engineering,

Pondicherry Engineering College,Puducherry-14

[1]Research Scholar, Dept. of EEE, Pondicherry Engineering College, Puducherry, India
[2]Assistant Professor, Dept. of EIE, Pondicherry Engineering College, Puducherry, India
[3] Professor, Dept. of EIE, Pondicherry Engineering College, Puducherry, India

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1. Introduction

There are many process models available for pH process. One such model is HammersteinWiener model. It was used to model a steam temperature[1] in distillation system by using system identification where three nonlinear models such as Hammerstein model, a Wiener model and a Hammerstein-Wiener model have been compared. All the models have been optimized with respect to initial state, search criterion and number of iterations. Among three model tested, it was found that the most accurate model is the Hammerstein Wiener model with piecewise linear and sigmoid network estimators.A maximum likelihood based method[2] for identification of the Hammerstein Wiener model structures was also described. Identification of the parameter values for Hammerstein Wiener systems was done were both process noise and white noise had been considered.

A nonparametric Hammerstein model[3] based model predictive control approach for the regulation of heart rate during treadmill exercise was also dealt. A quality of service performance management [4] and resource provisioning by using an off-line identification of Hammerstein and Wiener nonlinear block structural model was also described. Using the characteristic structure of the nonlinear model a predictive feedback controller based on a gain schedule technique is incorporated in the design to achieve performance in complex software system. A Hammerstein Wiener nonlinear model and the box Jenkins linear models[5] for silage temperature variation prediction prior to the decomposition process was also done. The estimated Hammerstein Wiener model was also capable of detecting abnormal temperature variations caused by the decomposition process and it outperforms other nonlinear models such as nonlinear ARX, Wiener.

The Wiener model[6] was also used as an internal model for nonlinear model predictive control of the pH neutralization process. A WienerLaguree model[7]was also used to evaluate identification of a pH neutralization process. The identified WienerLaguree model was used for Nonlinear Model Predictive Control and is based on the sequential quadratic algorithm. A nonlinear controller based on Wiener model[8] was also designed to control the pH of a time delayed pH system.Nonlinear systems represented by linear models along with structured or unstructured uncertainties using Wiener or Hammerstein model[9] and applying robust control strategies using MPC was found to reduce computational complexities. It was also found from study that not much contribution was done for control of pH process using Hammerstein Wiener model.

This paper deals about developing a model that best fits the process and use it for identification of process. The model that has less loss function value and less final prediction error(FPE) value is identified. This model can support for best control actions when a nonlinear controller based on model nonlinear characteristic is used. Hence a new controller based on Hammerstein Wiener model is proposed as Hammerstein basedModel Predictive Controller (HMPC) that can perform better than other model based controller for pH process.

2. Process Modeling

pH process is a highly nonlinear process and it is time invariant. The typical strong acid-strong base system is modeled as suggested by [10] McAvoy, where material and ionic balance gives a set of linear differential equations and a nonlinear algebraic equation.Material balances in the reactor can be given by

$$V\frac{dx_a}{dt} = F_aC_a - (F_a + F_b)X_a \quad (1)$$

$$V\frac{dx_b}{dt} = F_bC_b - (F_a + F_b)X_b \quad (2)$$

$$x_a - x_b + 10^{-pH} - 10^{pH-pkw} = 0 \quad (3)$$

where x_a and x_b are state variables and F_a is the flow rate of the influent acid stream, F_b is the flow rate of the titrating base stream, C_a is the inlet acid concentration , C_b is the inlet base concentration, V is the volume of the mixture in the CSTR as shown in fig.1.

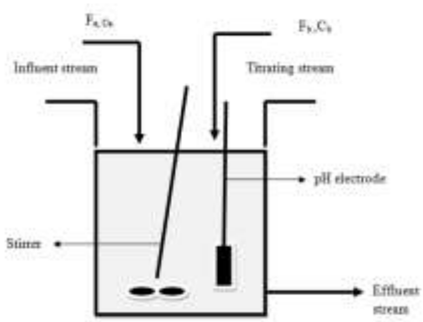

Fig.1 pH neutralization Process

The nominal value taken for modeling of pH process model are volume of the reactor (V)=5.7L, inlet acid concentration (Ca)=0.2mol/L, inlet base concentration (Cb)=0.2mol/L, flow rate of process acid stream (Fa)=20L/h.

3. Estimation of Process Model

Sample data's are estimated and analyzed using system identification in order to find best model fit for different nonlinearities as shown in Fig.2using equation (1) to (3)

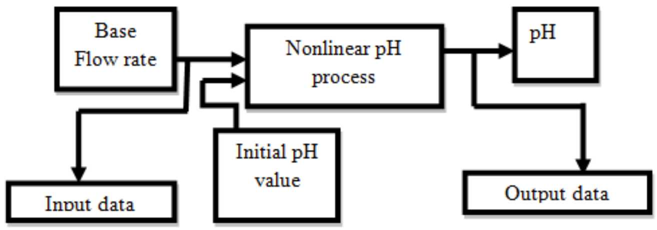

Fig.2 Diagram for estimation of pH model in simulink

Parameters of linear block and nonlinear block are estimated for the Hammerstein Wiener model. The model fit, FPE and loss function values are compared for different nonlinearities. The input to the pH process is base flow rate u_1 and output is pH y_1.Fig.3shows the input data and the corresponding output data for random change in flow rate.

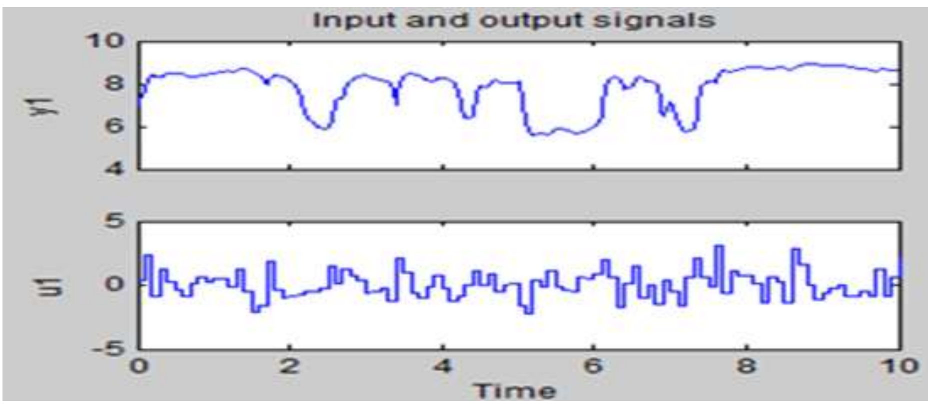

Fig.3 Input and output data

Totally 10000 data samples are considered for model identification. The output response for identification of Hammerstein Wiener model for different nonlinearities is shown in Fig.4.

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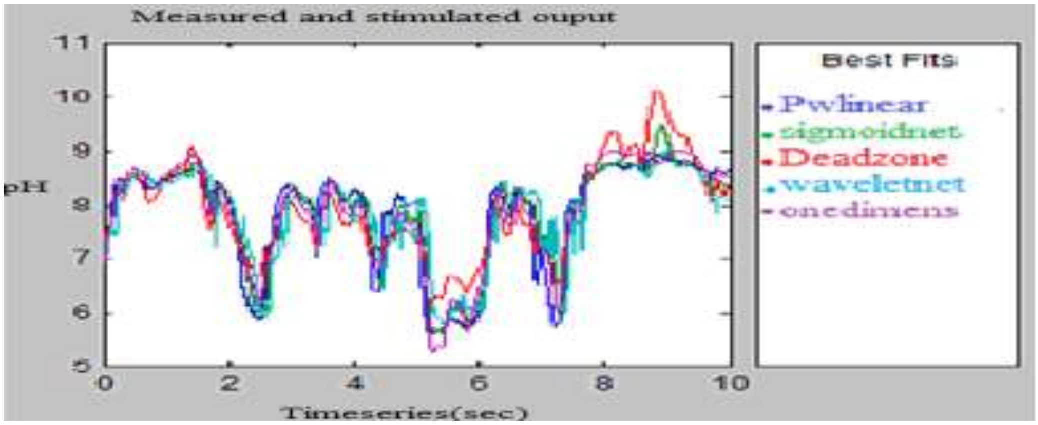

Fig.4 Output response of HammersteinWiener model

In Fig.4 the comparison of all the nonlinearities are shown. A Hammerstein Wiener model has a dynamic linear element with poles ,zeros and delay and two nonlinear static element expressed as input nonlinearity and output nonlinearity. Here a Hammerstein Wiener model with (zeros-2 poles-3 delay-2sec) is modelled as shown in table 1. From Table 1, it can be found that the best Hammerstein Wiener model is the model that has a model fit of 92.84, loss function value of 0.02365 and final prediction value of 0.02366 when dead zone and piecewise linear are used as input nonlinearity and output nonlinearity respectively.

Table 1 Using Linear Model With Zeroes -2 Poles -3 Delay-2 Sec

Input Nonlinearity	**Output Nonlinearity**	**Model Fit(%)**	**Loss Function Value**	**FPE**
Saturation	Piecewise Linear	92.84	0.0236	0.0239
Dead zone	Piecewise Linear	92.84	0.02365	0.02366
Saturation	Sigmoid Network	91.66	0.03208	0.03211
Saturation	Wavelet Network	90.84	0.03863	0.03866
Dead zone	Wavelet Network	77.44	0.2348	0.235
Sigmoid	One dimensional polynomial	54.06	0.9734	0.9742
Sigmoid	Piecewise Linear	53.13	1.012	1.013

A Hammerstein Wiener model with zeroes-2 poles-3 delay-1sec as shown in table 2 was modeled that has a maximum model fit of 90.33, loss function value of 0.0431 and final prediction value of 0.04314 when saturation and sigmoid network used as input nonlinearity and output nonlinearity respectively.

Table 2 Using Linear Model With Zeroes -2 Poles-3 Delay-1sec

Input Nonlinearity	**Output Nonlinearity**	**Model Fit (%)**	**Loss Function Value**	**FPE**
Saturation	Sigmoid network	90.33	0.0431	0.04314
Dead zones	Piecewise linear	86.55	0.08448	0.08453
Dead zone	Sigmoid network	74.57	0.2987	0.299
Wavelet network	Piecewise linear	54.7	0.944	0.9451
Saturation	Wavelet network	43.24	1.51	1.518
Piecewise linear	One dimensional polynomial	32.65	2.09	2.091

A Hammerstein Wiener model l with zeroes-3 poles-3 delay-1sec as shown in table 3 was modeled that has a maximum has a best model fit of 97.7, loss function value of 0.001148 and final prediction value of 0.001147 when dead zone and piecewise linear used as input nonlinearity and output nonlinearity respectively.

Table 3 Using Linear Model With Zeroes -3 Poles-3 Delay-1sec

Input Nonlinearity	**Output Nonlinearity**	**Model Fit (%)**	**Loss Function Value**	**FPE**
Dead zone	Piecewise linear	97.7	0.001148	0.001147
Saturation	Piecewise linear	97.75	0.002324	0.002323
Dead zone	Wavelet network	86.78	0.08065	0.08072
Saturation	One dimensional polynomial	55.33	0.9192	0.9193

Sigmoid Network	Piecewise linear	51.73	1.073	1.074
One dimensional polynomial	Saturation	44.6	2.175	2.17
One dimensional polynomial	Dead zone	40.99	1.949	1.944

Similar analysis was done to find the best fitting model and itscomparison table is shown in table 4, where z represents zeros, p represents poles and d represents delay.

Table 4 Comparison for Different Nonlinearity based on Different Orders

ORDER			**INPUT NONLINEARITY**	**OUTPUT NONLINEARITY**	**MODEL FIT (%)**
z	**p**	**d**			
2	3	1	Saturation	Piecewise linear	98.42
3	3	1	Dead zone	Piecewise linear	97.92
3	3	1	Saturation	Piecewise linear	97.75
2	3	2	Saturation	Piecewise linear	92.84
2	3	2	Dead zone	Piecewise linear	92.84
2	3	2	Saturation	Sigmoid network	91.66
2	3	2	Saturation	Wavelet network	90.84

It was found that the model with order of 2 zeroes 3 poles and 1secdelay with saturation as input nonlinearity and piecewise linear as output nonlinearity has a best model fit of 98.42% ,final prediction value as 0.001148 and loss function value as 0.001147. Hence this model is used to develop the controller. This model that maximum fits is used to control the pH process using Hammerstein based Model Predictive Control(HMPC).

4. Hammerstein Based Model Predictive Controller(HMPC)

For highly nonlinear process the performance of MPC based on linear model can be poorer when comparing to nonlinear controller. In order to overcome this problem Hammerstein based Model Predictive Controller (HMPC)

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has to be implemented as shown in Fig 5,6 to remove the nonlinear part from the process to support fast and smooth control action by including the nonlinear inverse part (N-L inverse) to make the control resemble as linear control.

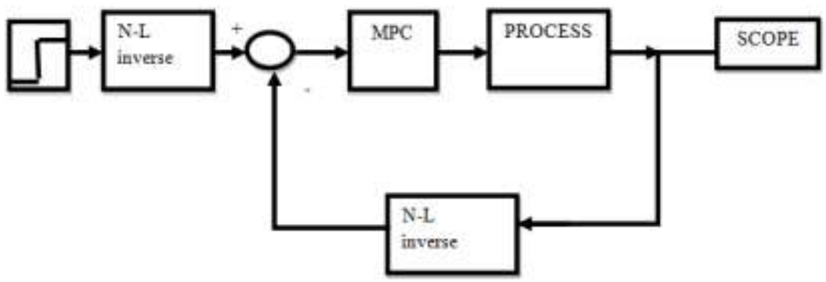

Fig.5 Hammerstein based Model Predictive Controller

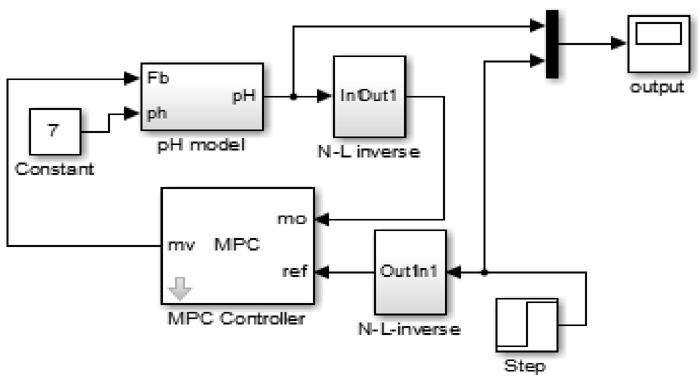

Fig.6Simulink block of HMPC controller

The inverse of nonlinear element known as piecewise linear of Hammerstein model is incorporated with the Model Predictive Controller for controlling highly nonlinear pH process.

5. Simulation Results

Sample time taken for Hammerstein based Model Predictive Controllerwas0.01 with weight tuning as 0.8 and control and prediction horizon as 2 and 10 respectively. Comparison is done among the Model Predictive Controller and Hammerstein model predictive control(HMPC) to find the best controller.

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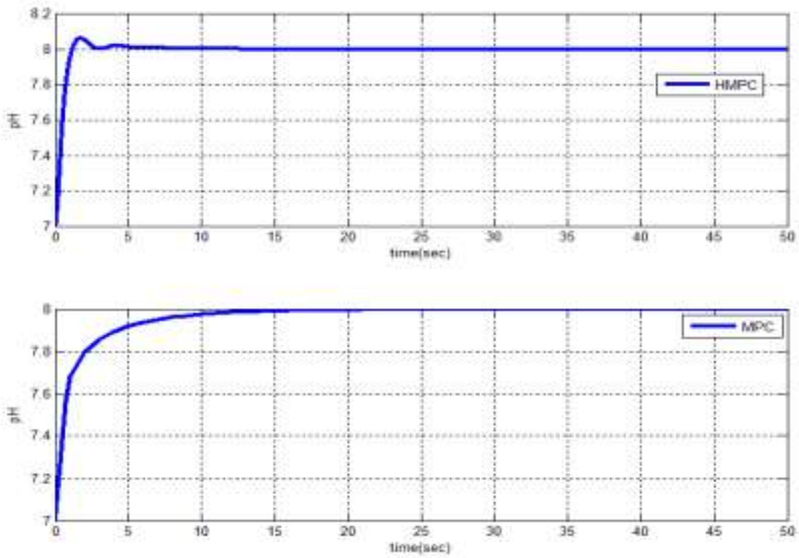

Fig.7 Comparison of Hammerstein based Model Predictive Controller and local Model Predictive Controllerfor step change from pH7 to pH 8

From the fig.7, it is found that the Model Predictive Controller based on Hammerstein Wiener model outperforms Model Predictive Controller by showing less rise time and less settling time for set point change from pH7 to pH8.

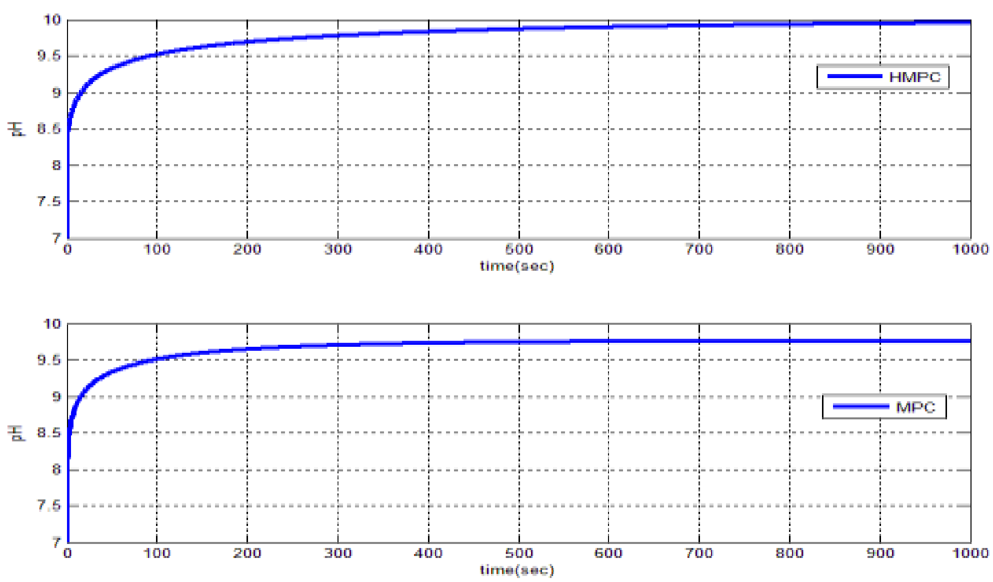

Fig.8 Comparison of Hammerstein based Model Predictive Controller and local Model Predictive Controller for step change from pH7 to pH 10

From the fig.8, it is also found that the Model Predictive Controller based on Hammerstein Wiener model outperforms Model Predictive Controller by showing less rise time and less settling time for set point change from pH7 to pH10.

Table 5 Comparison of ISE , IAE Values for Hammerstein Based Model Predictive Controllerand Local Model Predictive Controller

Local Model Predictive Controller(MPC)			**Hammerstein based Model Predictive Controller for pH process (HMPC)**		
Step change	**ISE value**	**IAE value**	**Step change**	**ISE value**	**IAE value**
7-8	7.649	15.23	7-8	2.043e-05	0.02034
8-9	25.12	36.08	8-9	6.677e-05	0.0365
9-10	141.1	208.9	9-10	0.0003351	0.2905
10-11	656	537.3	10-11	0.001543	0.8073
11-12	1837	933.4	11-12	0.00429	1.416

As shown in Table 5 for anystep change the ISE and IAE values for Hammerstein based Model Predictive Controller is low when compared with Model Predictive Controller and hence it can be concluded that HMPC is better than MPC for pH process.

6. Conclusion

pH process is identified using HammersteinWiener model by analyzing model fit ,loss function value and final prediction value for different types of nonlinearities. The best Hammerstein Wiener model was identified that has model fit of 98.42% with less loss function value and final value prediction and is chosen for study of MPC controller using HammersteinWiener model. It is found that for highly nonlinear process the performance of MPC based on linear model can be poorer. In order to overcome this problem the nonlinear part taken from Hammerstein Wiener model is incorporated with Model Predictive Controller known as Hammerstein Model Predictive Controller (HMPC) and has been implemented. The performances of Hammerstein Model Predictive Controller are compared and found to outperform linear Model Predictive Controller.

References

[1] Tatang Mu Iyan a, Mohd Nor Mohd Than, Noor Adzmira Mustapha.,"Identification of Heat Exchanger QAD Model BDT921 based on Hammerstein-Wiener Model*", International Seminar on the Application of Science and Mathematics*, pp. 1-7,20ll.

[2] Adrian Wills, Thomas B. Schonb, Lennart Ljung, Brett Ninness, "Identification of Hammerstein-Wiener Models", *ELSEVIER Automatica*, vol. 49, pp. 70-81, October 2011.

[3] Steven W. Su,Shoudong Huang, Lu Wang , "Nonparametric Hammerstein model based Model Predictive Controller", *Proceedings of the 29th Annual International Conference of the IEEE EMBS Cite International ,Lyon,France*,August 2007.

[4] Tharindu Patikirikorala, Liuping Wang, Alan Colman, Jun Han. "Hammerstein-Wiener Nonlinear Model based Predictive Control for Relative QoS Performance and Resource Management of Software Systems", *ELSEVIER-Control Engineering Practice*, Vol.20, pp. 49-61, October 2011

[5] Esmaeil S. Nadimi. Ole Green. Victoria Blanes-Vidal. Jakob J. Larsen, Lars P. Christensen., "Hammerstein-Wiener Model for the Prediction of Temperature Variations inside Silage Stack Bales using Wireless Sensor Networks", *ELSEVIER Biosystems Engineering*, Vol .112, pp. 236-247, May 2012.

[6] Qing-chao Wang, Jian-zhong Zhang, "Wiener Model Identification and Nonlinear Model Predictive Control of a pH Neutralization Process based on Laguerre Filters and Least Squares Support Vector Machines", *Journal of Zhejiang University*, Vol. 12, no. I, pp. 25-35, May 2011.

[7] Sanaz Mahmoodi, Javad Posthan, "Nonlinear model predictive control of pH neutralization process based on Wiener Laguree model",*ELSEVIER-Chemical Engineering Journal* 2009, pp. 328–337.

[8] D. Swati, V.S.R. Rao, R. Pickhardt, M. Chidambaram, "Nonlinear PI Controller for Time Delayed pH System", *Indian Chemical Engineer*,Vol. 50 No. 2 April-June 2008, pp. 93-105.

[9] FatemehKhani, MohammadHaeri, "Robust model predictive control of nonlinear processes represented by Wiener or Hammerstein models" ,*Chemical Engineering Science*, Vol. 129(16) June 2015, Pages 223-231.

[10] McAvoy, T.J.,Hsu and Lowenthal . S, "Dynamics of pH in a controlled stirred tank reactor",*Ind. Eng.Chem.Process Des.Dev.*,Vol 11,1972,pp.68-70.