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NONLINEAR MODEL PREDICTIVE CONTROL OF A PILOT DISTILLATION COLUMN. AN ARTIFICIAL INTELLIGENCE APPROACH

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Abstract – In the last decade there has been a growing interested concerning nonlinear model predictive control (NMPC). However, the number of practical implementation of modern NMPC techniques is still very small due to the difficulties that have to be overcome to develop a practical implementable NMPC controller. In this paper the real-time implementation of a NMPC technique to a laboratory azeotropic distillation column is considered. The particular control hardware of the pilot distillation system leads to a hybrid control architecture. In this paper a novel control approach based on artificial intelligence techniques is introduced for hybrid systems. The control algorithm exploits the advantageous properties of genetic algorithm (GA) in the solution of the mixed real-binary optimization problem from the controller. This approach is used in conjunction with an artificial neural network (ANN) model in the NMPC (GANMPC) for enhanced computation. The approach is tested on a laboratory equipment, leading to good control performance in the real system.

Keywords: nonlinear model predictive control, neural network based control, genetic algorithm, hybrid control systems, azeotropic distillation control.

1. INTRODUCTION

Model predictive control (MPC) is one of the most widespread advanced process control techniques in the chemical industries [10], [12]. The main idea of MPC algorithms is to solve an optimization problem in order to find the control vector trajectory that optimizes a performance objective over a future prediction horizon. Predicted values of the controlled parameters are obtained from a process model. In most of the applications predictive controllers are based on linear models for prediction because of the numerous techniques available for identification and control movement calculation [2]. However, most of the chemical processes are highly nonlinear, with widely varying operating conditions, for which linear model predictive control (LMPC) sometimes does not lead to satisfying results. A direct extension of the LMPC is obtained when a suitable nonlinear model of the process is used for prediction instead of the linear one [1], [5], [7], [9], [11]. Artificial neural network (ANN) models have been widely used for nonlinear model predictive control. Their universal approximation property, together with their parsimony, make the latter attractive candidates for performing such tasks [4]. However when the

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process presents the special characteristics of hybrid systems, the implementation of NMPC techniques is even more difficult. In this paper a novel hybrid NMPC approach is presented and practical results are shown for the implementation to a nontrivial process, namely an azeotropic distillation column of ethanol-water mixture. For control an LV configuration is used, i.e., the reflux flow on the tray in the top (L) the vapor flow from the reboiler (V), respectively, are used as control inputs. The vapor flow is manipulated through the power of the reboiler that can take any arbitrary value, while the reflux flow is fixed using a bipositional valve. This special hardware leads to hybrid control architecture. In this structure one of the control inputs can take any real value between the certain hard limits, while the other one can take only binary integer values (corresponding to the open and closed position of the valve). This so called mixed logical dynamical (MLD) form of the model further increases the difficulties of the NMPC implementation. In the literature there is a large number of studies related to hybrid control architectures [6]. These approaches all use classical optimization techniques to solve the mixed integer quadratic program (MIQP) arisen in the on-line optimization from the hybrid controller. Although, with recent extension of the branch-and-bound optimization algorithms to MIQP, promising results were obtained, the solution of this type of optimization is still a challenging problem. In this paper a novel approach based on genetic algorithm (GA) [3] is proposed to solve the MIQP in the hybrid NMPC.

An input-output ANN model of the distillation column was derived with a specific topology to correspond to the hybrid control structure. To obtain an ANN model with good generalization properties a special training algorithm with Bayesian regularization was used [8]. The obtained ANN model was introduced and used for prediction in the NMPC controller. It was shown that the computational time necessary to solve one open-loop optimization problem in the controller is low enough to ensure real-time feasibility and fairly good control performance can be achieved.

2. EXPERIMENTAL SETUP

The experimental measurements were obtained in an ILUDEST bubble cap tray column. This equipment has the following characteristics: 30 practical plates; operation volume 10 liters; reboiler with a 2 kW capacity quartz heating rod; column head with solenoid controlled reflux-withdrawal divider and condenser of 0.2 m^2; distillate cooler (cooling agent – water); feed heating system with quartz heating rod, capacity 0.5 kW; product receivers 5 liters capacity each, to store the feed mixture respectively to collect the bottom and head product; diaphragm pumps for feed and bottom product withdrawal; 39 sampling valves on every tray, for feed, bottom, and distillate flows.

Experiments were conducted to capture the dynamic characteristics of the column. In experiments an ethanol/water mixture was used. This mixture forms an azeotropic mixture leading to a much more difficult modeling problem than for ideal mixtures.

In the development of the software interface the actual communication with the distillation plant is realized through the ILUDEST-MOS unit on the first level. In this way a hierarchical control structure with tasks distributed on two levels was implemented. This is necessary to ensure the safety operation of the plant in case of computer failure. For safety operation besides the hierarchical control structure, additional safety functions were implemented in the software.

The comunication between the PC and ILUDEST-MOS unit is established via the serial port of the computer using the RS-232 protocol, using a certain command protocol. The hybrid NMPC controller is implemented in MATLAB, and the control problem is solved, using the MATLAB GA toolbox developed by the authors. For this purpose, at every sampling time, the measurements are sent to MATLAB using the Dynamic Data

Exchange (DDE) possibility in Windows environment. The controllers, using the acquired data from the plant, solve the control problem and send the obtained control actions into the process through to the LabVIEW application.

3. ANN MODEL BASED CONTROL OF THE AZEOTROPIC DISTILLATION COLUMN

The control inputs considered were the sump heat power (Q_w) and the reflux rate (R). The controlled parameters were the temperatures on trays 3 and 25. The classical control algorithms cannot be directly implemented to the above-described laboratory distillation plant, due to the particular nature of the reflux valve. This equipment is a bipositional valve. When the valve is open the entire liquid flow from the condenser is extracted from the system as the distillate, and when the valve is closed it is reintroduced in the column as the reflux flow. Consequently, this device is a digital one; hence, it does not allow the implementation of any analog value for the reflux flow rate given by any analog control algorithm.

In this section hybrid control architecture is suggested for the pilot distillation plant. According to this control algorithm, one control input (Q_w) is an analog input which can take any value in the interval of 0-100%. The second, digital control input R, is derived and implemented through the special approach described in the next paragraphs.

Within the sampling interval T_s, a smaller sampling interval δ_s is considered, such that $N\delta_s=T_s$, with $N\in\mathbb{R}$. The digital control input will be a vector of the form:

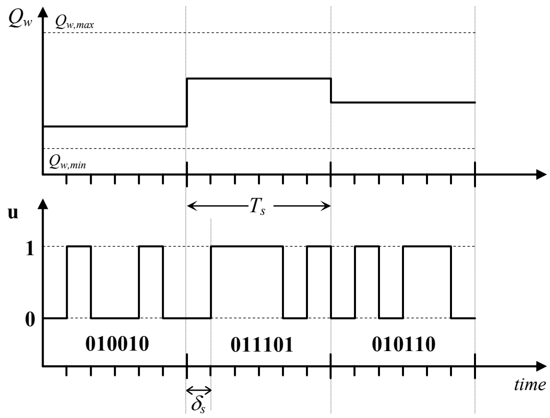

Fig. 1. *The proposed hybrid structure of the control inputs*

$$\mathbf{u}=\left[u_1,u_2,\ldots,u_N\right], \qquad \text{with} \qquad u_j\Big|_{j=\overline{1,N}}=\begin{cases}0 & \textit{if the valve is closed (reflux)}\\ 1 & \textit{if the valve is open (distillate)}\end{cases}. \tag{2}$$

The control value $u_j = 0$ means that the reflux valve is closed for a period of δ_s between moments $(j-1)\cdot\delta_s \le \tau < j\cdot\delta_s$ from the sampling period of T_s. The schematic representation of the control inputs for the proposed hybrid system is depicted in Figure 1. The optimization problem from the controller, that have to be solved on-line in each sampling period T_s is the following:

$$J\left(Q_w,\mathbf{u}\right)=\sum_{k=1}^{P}\left[\lambda_1\cdot\left(T_3(k)-T_{3,s}(k)\right)+\lambda_2\cdot\left(T_{25}(k)-T_{25,s}(k)\right)\right]^2, \tag{3}$$

$$\min_{Q_w\in\mathbb{R}^q;\,u_j\big|_{j=\overline{1,N}}\in\{0,1\}}\left(J\left(Q_w,\mathbf{u}\right)\right), \tag{4}$$

where $\lambda_{1,2}$ are weight coefficients $T_{3,s}$ and $T_{25,s}$ are the setpoints for the temperatures on trays 3 and 25 respectively, and P is the prediction horizon, $\mathbb{R}^q$ is the subdomain of real values from the interval [$Q_{w,min}$, $Q_{w,max}$], and $u_j\big|_{j=\overline{1,N}}\in\{0,1\}$ are the binary values of the control inputs in the interval T_s. The optimization problem described by equations (3)-(4) represents a special mixed real and integer optimization problem. The parameters to obtain from the solution of this problem are formed from one real value Q_w and N binary integer values u_j. The solution of such optimization problems represents a great numeric challenge. The special structure of the problem can be exploited very well if genetic algorithm (GA) is used

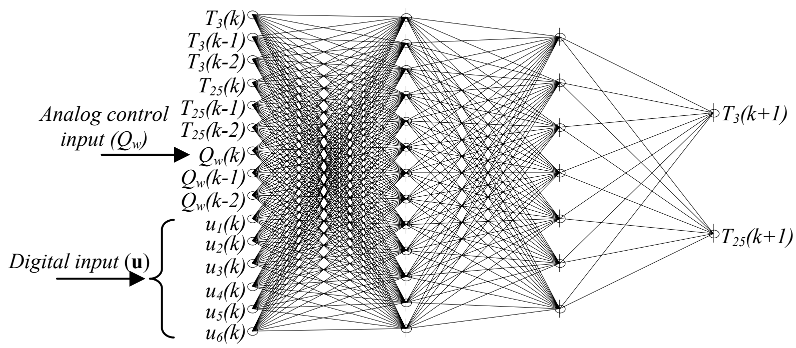

Fig. 2. *The ANN model structure for the hybrid control scheme*

to solve the optimization. Its feature to use binary representation of the optimization parameters to solve the optimization makes it an alluring tool for this kind of problem. For the genetic algorithm we may consider only two parameters to obtain from the optimization. The first is the real Q_w value, which can be coded on 16 bits to have the necessary precision in the real interval $[0, 100] \subset \mathbb{R}$, from which this control input may take values.

The second optimization state **u**, can be considered as a binary value from the interval $\mathbf{u} \in [\underbrace{000...0}_{N}, ..., \underbrace{111...1}_{N}]$. The obtained binary value for the Q_w is decoded in the real representation to be implemented in the process, while the binary **u** is interpreted in binary form. Every bit from **u** corresponds to the appropriate reflux valve position (0=*closed*; 1=*open*).

The special control algorithm described above was implemented in the developed software interface. For prediction in the NMPC a special ANN architecture was proposed. A sampling time of $T_s = 30s$ and a discretization interval for the digital control input $\delta_s = 5s$ were used. This means that there are 6 (6*5 s = 30 s) digital points in the sampling interval T_s. The digital input **u** will thus be represented as a 6 digit binary number. For example a control **u** = **100110** means that the reflux valve is open for 5 s after that it is closed for 10 s, opened again for 10 s, and finally closed for 5 s.

The structure of the feed-forward network used to model the system is presented in Figure 2. The current and 2 past values of the controlled outputs (T_3 and T_{25}) and analog control input (Q_w), and the current value for the digital control input **u,** were used. For every bit from **u** an input neuron is used in the ANN model. Two hidden layer with 13 and 7 neurons respectively were used, with the *logsig* transfer functions. In the output layer the *purelin* transfer function was used.

An experiment has been designed in which random values were used for the process inputs. The obtained experimental sequence was divided in two parts. The first part was used to train the network and the second part was used to test the generalization properties of the ANN model. The performance of the ANN model is presented on Figures 3 and 4 for the normalized training data, and on Figures 5 and 6 for the normalized testing data, respectively.

On these figure the ANN prediction (A) is represented versus the training data (T). The ideal case, when $A = T$ is also presented. Additionally, a linear regression equation of the form $A = aT + b$ is computed. In this equation the coefficients a and b are qualitative measures of how good is the network prediction. When a =1 and b = 0 the ideal prediction $A = T$ is obtained. In our case one can observe that although the a and b values are close to their ideal values and the correlation coefficient (R) is high enough, the prediction is not ideal. These results suggest uniformly distributed errors, which most likely are due to measurement errors. Thus, one should expect that the network would filter the noise and give fairly good prediction.

The ANN model based NMPC (ANNMPC) was implemented in the software interface. The optimization (with GA), and the control movement computation are performed in MATLAB. Using the ANN model presented above, a good control performance is achieved. The ANNMPC performance was assessed in the case of setpoint tracking. For this a setpoint change is applied to the system for both controlled parameter (T_3 and T_{25}) but in different moments. The results are shown on Figure 7. The results presented are obtained with controller parameters λ_1=λ_2=1, P = 20 (600 s), and control prediction horizon of M=1. A successive-recursive prediction algorithm is used to perform the $P > 1$ prediction.

The parameters of the GA used in the optimization are: 50 members in the population, cross-over probability = 1, mutation probability = 0.03, limits for the inputs $Q_w \in [0, 100]$, $\mathbf{u} \in [000000, 111111]$, codification bits = [16, 6], and maximum number of generation = 100. With these parameters one open-loop optimization was solved in less then 20s, which is smaller then the used sampling time, T_s = 30s. Consequently, the ANNMPC controller in the above-described structure is feasible for real-time implementation.

4. CONCLUSIONS

The practical implementation of an artificial neural network based hybrid nonlinear model based predictive controller (ANNMPC) to a nonideal azeotropic distillation column is presented. First the 30 trays ILLUDEST's pilot laboratory equipment is described. Next, the software interface developed by the author is presented briefly. This interface joins the

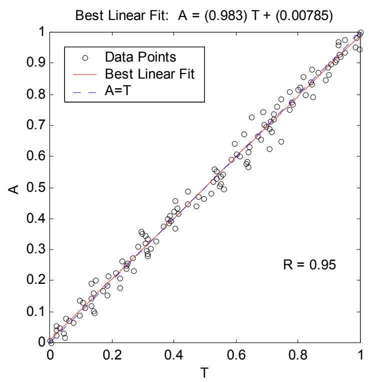

Fig. 3. *ANN prediction for the training data for T_3*

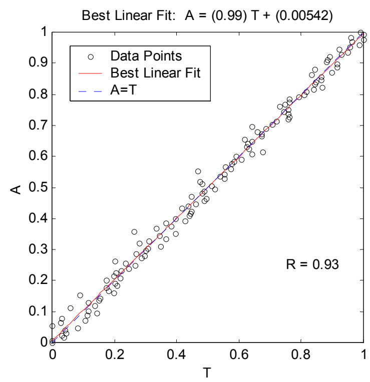

Fig. 4. *ANN prediction for the training data for T_{25}*

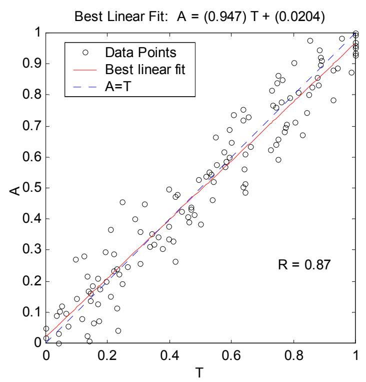

Fig. 5. *ANN prediction for the testing data for T_3*

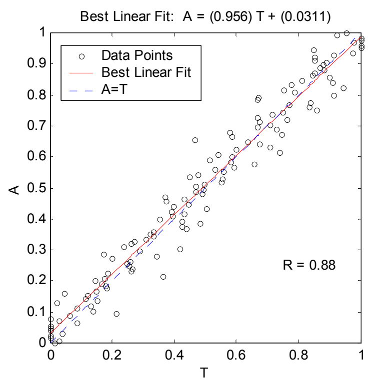

Fig. 6. *ANN prediction for the testing data for T_{25}*

two most important characteristics of computer interfaces: flexibility and safety operation.

For the control of the system a 2-inputs-2-outputs control architecture is considered. The control inputs were the sump heater power and the reflux rate, respectively, while the controlled outputs consists of temperatures on trays 3 and 25, respectively. The sump heater is an analog device while the reflux rate is set via a digital on/off reflux divider valve. This leads to a mixed binary-real optimization problem that needs to be solved on-line in the NMPC implementation. Because of these particular features of the equipment the control of the system is a challenging task. A novel hybrid control approach is proposed, which in combination with GA exploits the special structure of the control system.

An ANN model adapted to the special structure of the mixed logical dynamic system has been developed and used in the novel GA-hybrid control system, achieving good control performance in the real-time implementation.

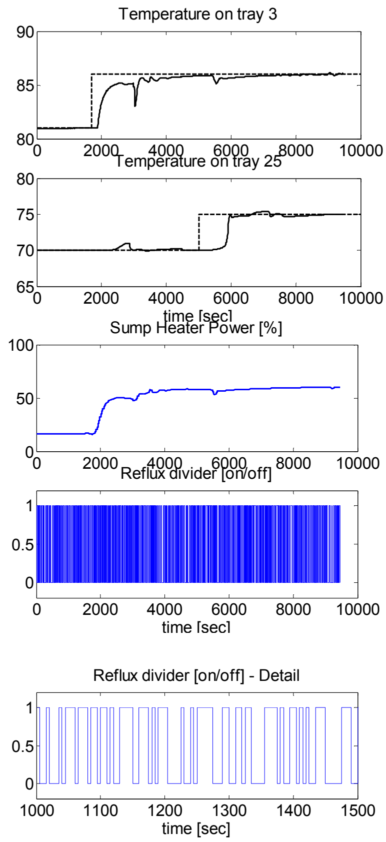

Fig. 7. *ANNMPC of the azeotropic distillation column*

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