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Adaptive Control of Distillation Column using Adaptive Critic Design

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***Abstract*—The paper aims at synthesis of an adaptive controller of the distillate output flow rate of a binary distillation column. The disturbance of the process is the change of concentration of the inlet compound. The Adaptive Critic Design (ACD) approach was applied to predict on time the future effect of disturbance and to adapt the distillate output flow rate in order to prevent deviations from the desired distillate concentration. The key element of ACD – the critic – is a fast trainable recurrent neural network named Echo state network (ESN). The simulation investigations demonstrated that the proposed adaptive control scheme outperforms a classical non-adaptive controller with respect to the settling time and the reaction delay.**

Keywords—adaptive control; Adaptive Critic Design; Echo state network; binary distillation column

I. INTRODUCTION

Distillation or fractioning columns are essential aggregates in many chemical industries [1]. They separate a liquid mixture of many compounds into its components called fractions based on the differences in individual component volatilities. The models describing these processes are good test cases for nonlinear process control.

In present study we adopted a nonlinear model [2] of such a plant (binary distillation column) in order to test our intelligent approach for adaptive control design, namely Adaptive Critic Design (ACD) [3]. Its aim is to train a predictor (called adaptive critic) of the future effect of the current input disturbance to the process state and to generate proper control actions preventing undesirable changes of the process output. The main difference with Model Predictive Control (MPC) and other approaches from the classical control theory is that ACD doesn't need complete information about all process state variables or a model or an observer of the plant. Instead it relays on a simplified signal in the form "good/bad" process condition. The control actions in reaction to such prediction are generated as attempt to minimize the future "bad" signal or to maximize future "good" signal solving dynamic programming task in forward manner.

The rest of the paper is organized as follows: next section presents the used technique – ACD and the recurrent neural network (Echo state network, or briefly ESN) in the role of adaptive critic element; section III presents the plant and the aims of its control; the simulation results are given in section IV; finally concluding remarks and plans for the future work finish the paper.

II. ADAPTIVE CRITIC DESIGN AND ECHO STATE NETWORK CRITIC

A. ACD approach

ACD [3] is considered as a method that approximates dynamic programming [4, 5] in an attempt to overcome its "curse of dimensionality". Its roots are in the biologically motivated "learning from experience" approach also known as Reinforcement Learning (RL) [6]. The neural networks (NN) are usually adopted as basic building elements in ACD due to their ability to learn from examples. So the ACD is also called "neuro-dynamic programming".

The basic scheme of ACD for process control is presented on Fig. 1. Its key elements are the "critic" – predictor of future outcomes or utility $U(k)$ that has to be optimized; and the "actor" – controller that generates actions $a(k)$. It is supposed that only part of the plant state variables (vector $x(k)$) are measurable.

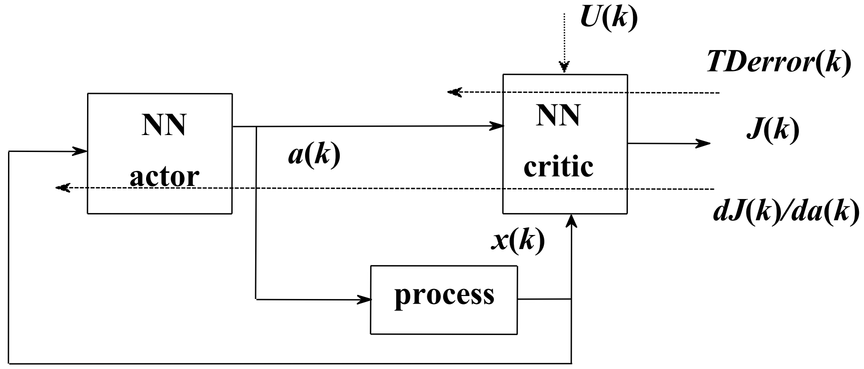

Fig. 1. Adaptive Critic Design for process control.

The main "trick" of the method is in training of the critic NN to predict future values of the utility function resulting from current actions (that is in fact approximation of the Bellman equation):

$$J(k) = \sum_{t=0}^{\infty} \gamma^t U(k+t) \qquad (1)$$

Here the parameter $\gamma \in [0, 1)$ is discount factor. Training of the critic NN is done according to the proposed in [7] algorithm that minimizes the "temporal difference (TD) error:

$$TDerror(k) = J(k) - U(k) - \gamma J(k+1) \qquad (2)$$

It is motivated from the brain ability to learn how to predict future outcomes on the basis of previous experience without awaiting the final results from the current actions.

Then, having well trained critic, the actor (controller) is adjusted so as to minimize/maximize critic predictions by gradient descent algorithm using backpropagation of critic output according to the chain rule for derivatives calculation [8].

The dashed lines on Fig.1 represent the propagation of the training signals for the critic and the actor respectively.

Numerous theoretical developments in this field during the last thirty years led to variety of adaptive and optimal control approaches [9]. In most cases the critic is trained off-line since it needs rich collection of data from several process runs exploiting possible work regimes of the plant. In some works [10] combination of off-line and on-line learning is also considered but for the true on-line applications very fast training algorithms are needed [11]. Moreover, for highly non-linear environments, such as industrial plants, usage of recurrent NN models so the on-line learning algorithms become additionally complicated.

In search of fast trainable NN architectures in [12-14] a recently developed class of Recurrent NN (RNNs) called Echo state network (ESN) [15] was adopted. The ESN incorporates a dynamic randomly generated reservoir of neurons and a fast trainable redout layer so that its on-line adaptation is possible via Recursive Least Squares (RLS) method [15]. Besides, the ESN structure facilitates the calculation of the needed derivatives [14].

B. Echo state network critic

ESNs belong to the group of RNNs included in the so called "reservoir computing" approaches [16]. Their basic structure is shown on Fig. 2.

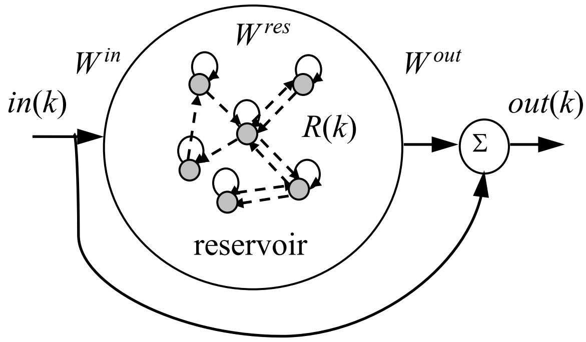

Fig. 2. Echo state network structure.

The ESN output vector for the current time instant k $out(k)$ (it will be $J(k)$ or $a(k)$ in the case of critic or action network respectively) is usually a linear function of its input $in(k)$ and the current reservoir state $R(k)$:

$$out(k) = f^{out}\left(W^{out}\left[in(k) \quad R(k)\right]\right) \qquad (3)$$

f^{out} is usually the identity function. The only trainable matrix W^{out} has size of $n_{out} \times (n_{in} + n_R)$, where n_{out}, n_{in} and n_R are the sizes of the corresponding output, input and reservoir state vectors.

The neurons in the reservoir have simple sigmoid activation function f^{res} (usually it is hyperbolic tangent) that depends on both input and previous reservoir state as follows:

$$R(k) = f^{res}\left(W^{in} in(k) + W^{res} R(k-1)\right) \tag{4}$$

Here W^{in} is $n_{in} \times n_R$ matrix of input weights while W^{res} is $n_R \times n_R$ matrix containing all recurrent connections in the reservoir. Both of them are randomly generated and are not trainable. There were developed different approaches for production of proper reservoir matrices [16]. Here we used the proposed in [17] approach called intrinsic plasticity (IP). It suggests initial adjustment of these matrices motivated by the aim to increase the entropy at the reservoir output. The training of the output matrix in present work was done by the RLS algorithm [15].

III. PROBLEM FORMULATION

A. Distillation column

The scheme of an industrial distillation installation is presented on Fig. 3.

It consist of a binary distillation column that separates the feed substance with concentration x_F entering the column with feed flow rate F into two main fractions: a target distillate product (the lightest product with lowest boiling temperature) with output concentration x_D and output flow rate F_D and a bottom product (the heaviest product with the highest boiling temperature) with concentration x_B and output flow rate F_B. In order to achieve better separation of the two substances such installations in industry have also reflux channels that return a part from both products on the top of the column. For this aim the liquid bottom product goes through the steam reboiler and evaporates while the upper product has to be cooled in the condenser reflux drum.

There are several control loops that ensure maintenance of the liquid levels of all vessels as well as desired concentrations of the output products.

Usually the control aims at achievement of desired concentrations of the two products (distillate and bottom). Since the input liquid that has to be separated usually comes from a previous stage of production, its concentration could vary in dependence on the conditions in previous installations. So it could be considered as the main cause of disturbance to the distillation process.

Hence the main aim of the adaptive control should be to react on time to this measurable disturbance in order to prevent undesirable changes of the output products concentrations.

B. ACD for binary distillation column

Following the main control aims of such installation, we define the following adaptive control problem to be solved: maintain the distillate concentration as close as possible to its set point $x_{Dset\ point}$ suppressing disturbances in the input concentration x_F. Hence the utility that has to be minimized is:

$$U(k) = \begin{cases} -0.1 & if \quad error < \theta_1 \\ 0 & if \quad \theta_1 \le error \le \theta_2 \\ +0.1 & if \quad error > \theta_2 \end{cases} \tag{5}$$

Here θ_1 and θ_2 determine the allowed interval for the error (it was +/-0.1% from the nominal state). Note that we don't need to account for exact error but only for its deviation from the allowed region.

Here we chose to adapt only controller for distillate output flow rate and to keep material balance in the column maintaining prescribed reflux ratio rr=const. as follows:

$$F_{reflux} = rr * F_D(k) \tag{6}$$

Since the critic in this case must be action dependent, its inputs are only the control action F_D and the disturbance x_F.

The actor (controller) determines the current output distillate flow rate via gradient descent as follows:

$$F_D(k+1) = F_D(k) - \alpha J(k) \frac{\partial J(k)}{\partial F_D(k)} \tag{7}$$

thus minimizing $J^2(k)/2$. Here α is parameter taking values between 0 and 1 that defines the learning rate.

IV. RESULTS AND DISCUSSION

In our simulation experiment we trained the ESN critic off-line. For this purpose we've generated training data set using the model from [2] and the corresponding software in Matlab [18]. We added a proportional (PI) controller for distillate output flow rate to the simulator and imitated the disturbances ranging from -1% to 1% deviations from the nominal value of input compound concentration. The collected step responses of the simulator are shown on Fig. 4, upper plot. The actions generated by the PI controller are shown on the lower plot of Fig. 4.

These data were used to train ESN critic iteratively starting with zero discount factor and slightly increasing it after each iteration. The training algorithm uses RLS and minimizes the temporal difference error.

Fig. 5 presents predictions from the trained critic in comparison with the utility function that is in the form of reinforcement signal ("good" – zero, "bad" – +/-0.1).

It is clear that the critic is able to predict "bad" signal (5) slightly before the distillate concentration goes outside the allowed region that was +/-0.1% around the set point.

Figures 6 and 7 represent simulations with trained critic and the adaptive controller (7) for disturbance of 1% above and below from the nominal value of the inlet flow concentration respectively.

Both figures demonstrated the ability of the trained critic (second plot) to predict deviations of the distillate concentration (first plot) from its set point right after the disturbance (third plot). The last plot on both figures resents the control action calculated according to equation (7) that compensates the disturbance thus minimizing the output error.

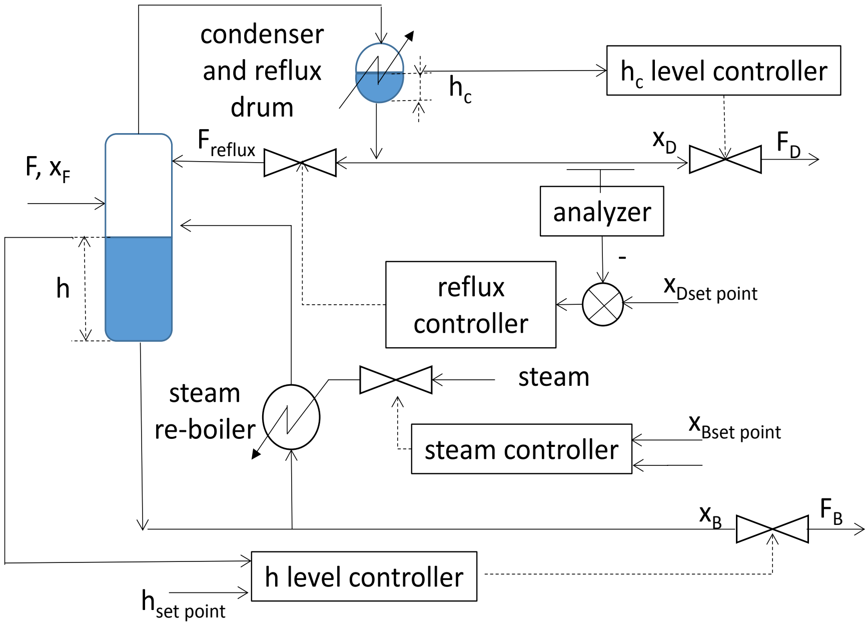

Fig. 3. Distillation column control scheme.

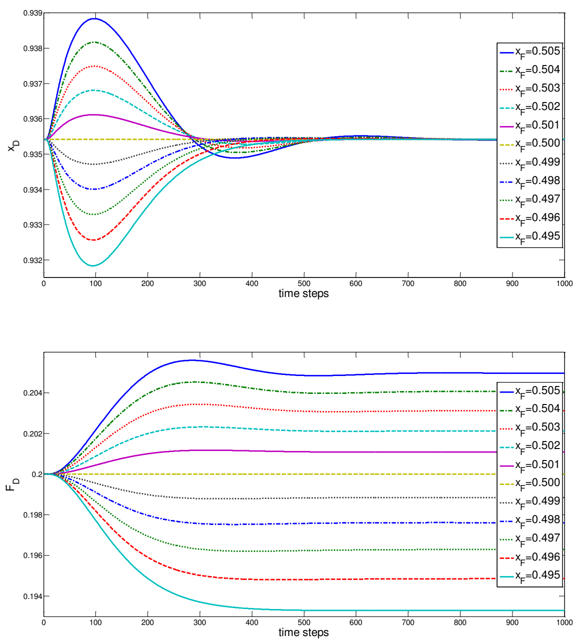

Fig. 4. Process response (upper plot) to step change disturbances at the concentration of input and corresponding PI controller actions (lower plot).

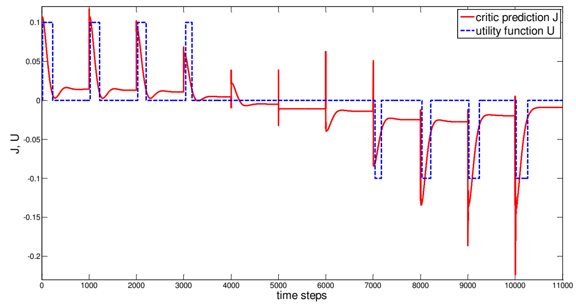

Fig. 5. Utility (U) and its prediction from the critic (J).

Figures 8 and 10 represent a “zoom” of the first 250 time steps of the simulated reaction of the plant output to the disturbance of +/-1% comparing the PI and ACD controllers. It was observed that the transient responses with ACD controller were faster and with less over/undershoots. This can be explained by the fact that the critic predicts the future deviations from the set point right after the disturbance was measured at the plant input so the ACD controller reacts at the beginning of the disturbance while the PI controller reacts after the disturbance effect on the output is detected, i.e. when the output error increases (figures 9 and 11).

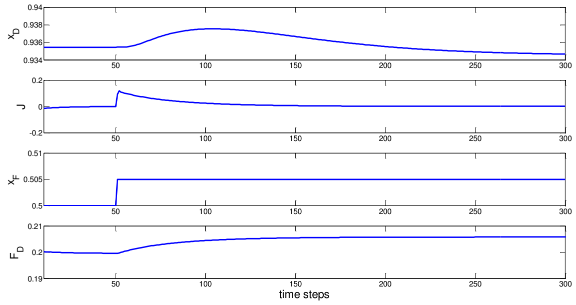

Fig. 6. Reaction of the ACD controller to the increase of inlet concentration.

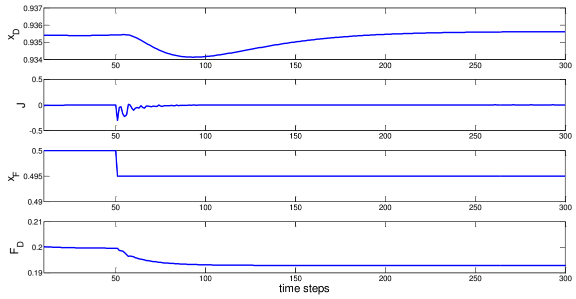

Fig. 7. Reaction of the ACD controller to the decrease of inlet concentration.

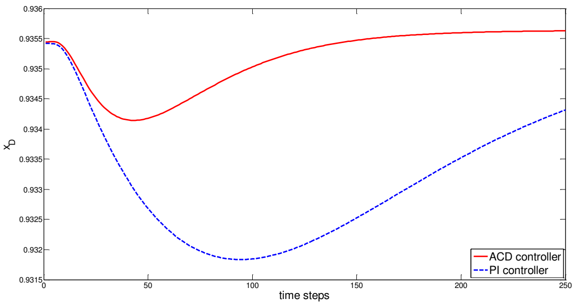

Fig. 8. Comparison between ACD and P controller for decrease of inlet concentration – distilate concentration.

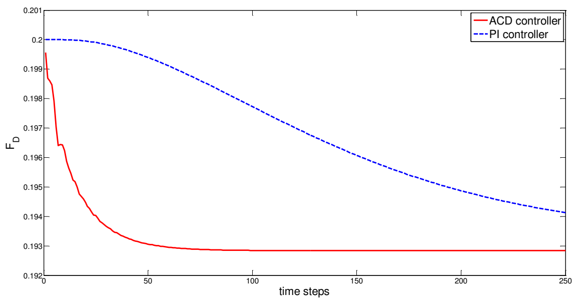

Fig. 9. Comparison between ACD and P controller for decrease of inlet concentration – distilate output flow rate.

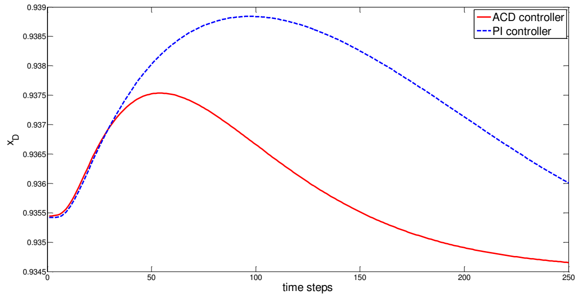

Fig. 10. Comparison between ACD and P controller for increase of inlet concentration – distilate concentration.

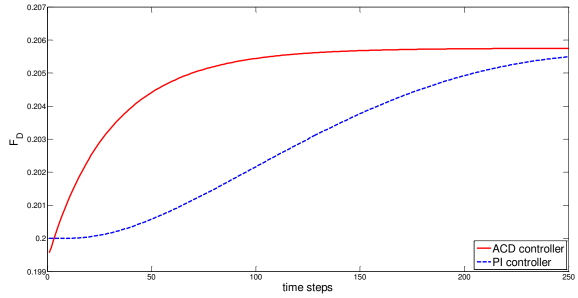

Fig. 11. Comparison between ACD and P controller for increase of inlet concentration – distilate output flow rate.

V. CONCLUSIONS

The conducted initial simulation experiments demonstrated that designed adaptive controller outperforms the classical controller with respect to settling time, over/undershoots and reaction time. Moreover, the ACD needs much less information to be designed in comparison with the conventional controllers that need detailed model of the plant and sophisticated mathematical techniques for their tuning.

The conducted simulation experiments with +/-1% disturbance could be easily extended to bigger changes of the inlet flow concentrations.

The presented simulation investigation is the first step towards implementation of ACD controllers into a more sophisticated distillation column simulator at the Petroleum-Gas University in Ploiesti. Next step will be implementation of on-line algorithm for training of adaptive critic aimed at accounting for variety of real situations with different kind of process disturbances.

ACKNOWLEDGMENT

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