Modeling and Control of an Experimental pH Neutralization Plant using Neural Networks based Approximate Predictive Control

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Abstract—**A nonlinear experimental pH neutralization plant is controlled using a neural networks based Approximate Predictive Control (APC) strategy. First a closed-loop identification is performed, further, using neural networks, a black-box modeling of the experimental plant is conducted. Then the approximate predictive controller is realized, where a linear model of the plant is extracted at each sampling period from the neural network model. This strategy is used to control the experimental neutralization plant for set point tracking and disturbance rejection.**

Index Terms—**pH Neutralization Plant, Neural Networks, Approximate Predictive Control**

I. Introduction

Monitoring and controlling the pH level is often performed in many chemical, industrial processes. It is important to improve the productivity and at the same time the robustness of these processes.

A PID controller is often used to deal with this process; however, it can only react to changes in a reference signal. On the other hand, a Model Predictive Control (MPC) approach is proactive and makes use of the information of the future reference signal which is usually known beforehand in a pH neutralization process. Although the MPC approach can not follow a step function directly it can follow it much better than a PID (justifiably assuming that the maximal possible slope of the change is the same). Furthermore a MPC approach is more sophisticated than a PID in terms of handling input and output constraints, as well as dealing with difficult system behaviors like high nonlinearity and long time delays, see e.g. [1].

Nonlinear Model Predictive Control (NMPC) is a well-established research approach to deal with nonlinear plants. Currently the NMPC is limited to processes with relatively slow dynamics due to the usage of nonlinear optimization approaches. Different techniques have been proposed to deal with this problem, see e.g. [2] and [3]. One of these techniques is the Approximate Predictive Control (APC) which uses a linearized model of the plant at each sampling period [4]. By this way, only a linear optimization problem has to be performed every sampling instant, this reduces the computational load and enables to deal with faster processes.

The APC approach is already known since more than ten years and some simulation studies were introduced in [5] to control gas turbine engines and in [4] for a pneumatic servomechanism. Although there is a vast literature on MPC in connection with neural networks there are not many applications of APC approaches based on neural network models used on real problem instances. One of the exceptions is the experimental 3-DOF Helicopter presented in [6].

To deal with the pH neutralization process in [7] a PID controller based on a neural network model is presented, which uses a genetic algorithm to tune the parameters of the PID controller offline on the nonlinear neural network model. In [8] on this problem an adaptive nonlinear control strategy is used.

Fig. 1. The experimental pH neutralization plant.

In this paper an APC strategy is used to control the experimental pH neutralization plant shown in Figure 1. We consider the set point tracking and disturbance rejection problem. All

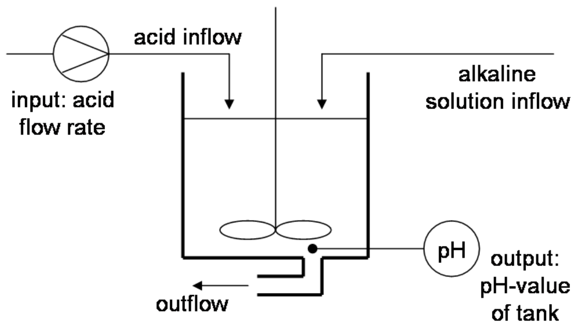

Fig. 2. Schema of the problem in its SISO arrangement.

these in order to assist the capability of APC to control such highly nonlinear process.

The rest of the paper is structured as follows: Section II describes the system under consideration. In Section III a system identification of the experimental pH neutralization plant is performed. Here a data set is collected in closed-loop and based on which a neural network is trained to represent the experimental plant. A short introduction to the APC strategy is given in Section IV. Section V presents the experimental results in terms of a set point tracking and a disturbance rejection problems. Finally in Section VI some conclusions are drawn.

II. Problem description

The pH neutralization process considered in this work is technically realized in a mixing tank with two input streams and one output stream. Figure 1 and Figure 2 show the experimental plant and a draft of it, respectively. The cylindrical tank is initially filled to three-fourths of its volume with water and the mixer is arranged in the lower fourth of the tank.

Separate control loops, one for the temperature and one for the liquid level, are used for holding the environmental conditions approximately constant. These controllers are simple On/Off-Controllers and as such are independent from the control method for the pH neutralization process.

One of the input streams is an alkaline solution (NaOH) and has a constant flow rate as well as a constant pH-value. The second input stream is acid (HCl) with a constant pH-value but its flow rate is manipulated to control the pH-value in the tank. The output stream is controlled in the mentioned separated On/Off-Control loop and hence the outflow is discrete depending on the liquid level within the tank. Finally a pH sensor is attached near the bottom of the tank precisely above the opening for the output stream. The reference signal which is a desired pH-value in the tank is known beforehand.

The whole system can be formulated as a SISO system: the pH-value of the liquid in the tank is the output and the acid flow rate is the input to this system. The right acid flow rate results in the desired pH-value within the tank. Insufficient acid results in an excessively alkaline pH-value; conversely, excessive acid inflow leads to an exceedingly acidic pH value.

In the following the nonlinearities of the experimental pH neutralization process are summarized:

- The neutralization process proceeds nonlinearly and has a high sensitivity around the pH-value of 7.
- The neutralization process has two regions of saturation: one in the very acidic (pH-value <5 approximately) and one in the very alkaline region (pH-value >9 approximately). If one of the regions is reached, it is very difficult to lead the pH-value out of the saturation.
- Although a mixer blends the liquids in the tank, a continuous homogenous distribution can not be reached immediately. One reason for this is the positions of the mixer relative to the location of the inflow stream, with the first being placed at the bottom of the tank, while the latter is found at the top.
- As a consequence of inhomogeneous liquid distribution, the liquid level, as well as other effects, the whole system has a noticeable time delay.

Furthermore the experimental build-up has some limitations:

- The available storage volume for the acid solution is limited and leads to a limitation of the measurement duration. Hence the data set which can be collected is relatively small.
- The pH sensors used have a measuring range from 0 to 14 pH, a smallest measuring range of 0.5 pH and an accuracy of $\pm$ 0.2%. This accuracy of the pH sensors defines the highest accuracy for the control.

III. System identification

To handle the nonlinear character of the plant a *black-box modeling* method is used. First the data has to be generated with which a neural network is then trained.

A. Data generation

For black-box modeling a set of input and output data must contain all important information about the behavior of the plant. To get all important information of a nonlinear system, the whole range of amplitudes and frequencies must be stimulated within which the plant shall be operated. The resulting data is a set of data input u_k and output y_k of the experimental plant with N being the number of samples k: $Z^N = \{u_k, y_k \mid k = 1, 2, \ldots, N\}$. Because of the saturation regions of the neutralization process the amplitude range of the pH-value which has to be covered is from around 5 to around 9.

With the *relay feedback method* [9] the critical frequency f_c; with different step responses the rise time t_r and finally using (1) the sampling frequency f_s and hence the sampling time T_s are determined as $f_c = \frac{1}{60}$Hz, $t_r = 90$sec and $T_s = 9$sec, respectively.

$$f_s = (5 \sim 10) \cdot f_c \quad and \quad f_s = (5 \sim 10) \cdot \frac{1}{t_r} \qquad (1)$$

A *multisine* signal [10] is used to excite the system. This is a periodic non-binary multifrequency signal given as:

$$u(t) = \sum_{i=1}^{n_s} A_i \cdot cos(\omega_i \cdot t), \quad (2)$$

where A_i and ω_i are the i-th amplitude and frequency of the multisine. With a multisine a desired frequency spectrum with constant amplitudes in a desired frequency range can be designed easily. Additionally a relatively small crest factor can be achieved (hence it has a good signal-to-noise ratio). Following [11] the minimum number of samples N and the minimum number of different frequencies n_s of the multisine can be computed by:

$$N \geq \frac{2 \cdot \pi \cdot \beta_s \cdot \tau_{dom}}{T}, \quad (3)$$

$$n_s \geq \frac{N \cdot T_s \cdot \alpha_s}{2 \cdot \pi \cdot \tau_{dom}}, \quad (4)$$

where τ_{dom} is the dominant plant time constant, β_s specifies how much low-frequency information will be in the signal and here it is chosen as $\beta_s = 3$ to get low-frequency information. The constant α_s denotes how much faster the closed-loop response is expected to be in comparison with the open-loop one, it is chosen as $\alpha_s = 1$. In addition, N and n_s are chosen as 350 and 20, respectively, which fulfil (3) and (4).

Figure 3 shows a typical spectrum of an input signal for the identification purpose, where f_n is the Nyquist frequency, f_b is the bandwidth of the closed loop system which is taken as $f_b = \frac{1}{60}$Hz with $f_b = \alpha_s \cdot f_c$. The low frequency part up to f_b stimulates the range in which the plant shall be operated. The amplitude of the high frequency part from f_b to f_n is only half of the amplitude of the low frequency part. Therefor, the high frequency noise is not significantly amplified.

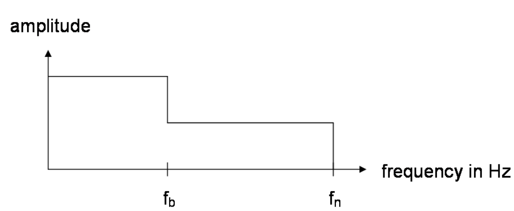

Fig. 3. The frequency spectrum of the input signal.

The closed-loop shown in Figure 4 is used to generate the data set for identification. By using the feedback control scheme one can force the output signal to get out of the saturation. This counteracts the problem of getting stuck in the saturation which otherwise occurs with the open-loop approach. A proportional controller is used in the closed-loop and the input signal is added just after the proportional controller. It is known that closed-loop identification based on a direct approach [10] is sensitive to noise since the noise of the input to the plant is correlated with the noise of the output; however, the high signal-to-noise ratio allows to assume that the amount of the noise in the output signal is neglectable.

The data set generated in this way is shown in Figure 5 and will be used in the following section for the training of the neural network.

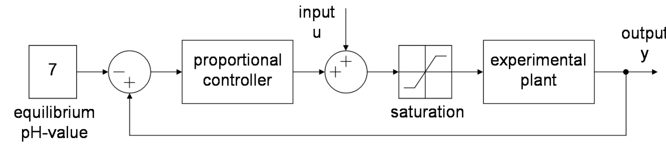

Fig. 4. Closed loop structure for the identification of the data set.

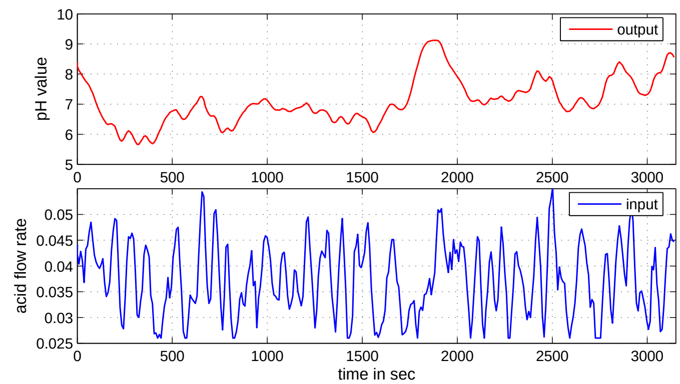

Fig. 5. Input and output signals of the training data set.

B. System identification with neural networks

A neural network is trained to capture the nonlinear behavior of the plant. The structure of the neural network is chosen to correspond to an ARX (AutoRegressive with eXogenous input) model structure in linear systems [10]. We refer to a neural network with this structure as a NNARX model structure, see Figure 6.

The input vector φ of the neural network consists of the past n output signals y_{k-1} until y_{k-n} and of the past m input signals u_{k-d} until $u_{k-d-m+1}$ which are shifted by the delay d. The output of the neural network is $\hat{y}_k$ which is a prediction of the plant's output at instant k. A *multilayer preceptron* neural network type is used [4], with two layers, p neurons and which is described as:

$$\hat{y} = f^2(W^2 f^1(W^1\varphi + \omega_0^1) + \omega_0^2), \quad (5)$$

where f^1 and f^2 are the tangent hyperbolic and linear functions, respectively, W^1 and W^2 are matrices containing the network weights and ω_0^1 as well as ω_0^2 are the weights of the biases. θ in Figure 6 contains all weights, i.e. it includes the weights W^1, W^2, ω_0^1 and ω_0^2.

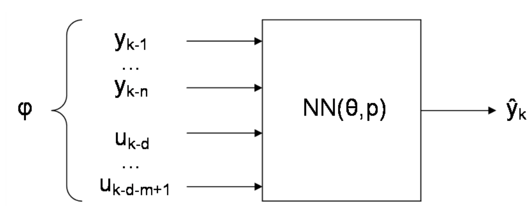

Fig. 6. NNARX model structure.

To train the network, i.e. to find the weights, the *Levenberg-Marquardt Backpropagation algorithm* [4] is used. The method

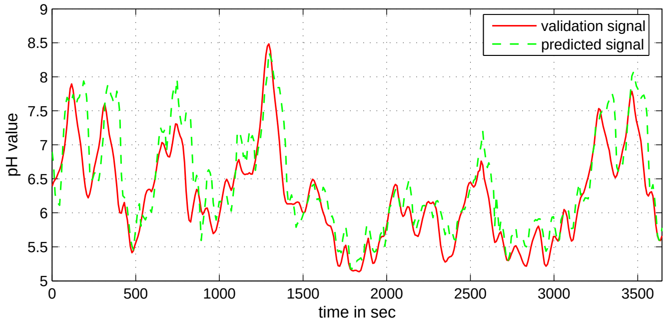

Fig. 7. Validation signal (solid) and 10-step-ahead prediction (dashed) of a NNARX model with $p = 11$, $n = 11$, $m = 10$ and $d = 1$.

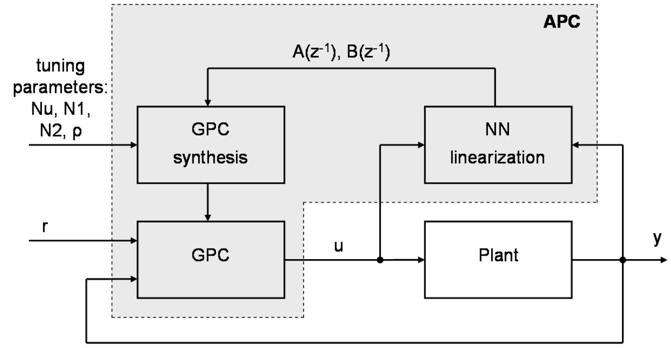

Fig. 8. Block structure of Approximate predictive control.

seeks to minimize the sum of the mean squared prediction errors given as:

$$V_N(\theta, Z^N, \alpha) = \frac{1}{2N}\sum_{k=1}^{N}((y_k - \hat{y}_k(\theta))^2 + \frac{1}{2N}\theta^T \cdot \alpha I \cdot \theta). \quad (6)$$

During the training of the neural network an undesired effect may occur, which is known as *overfitting* [4], [12]. In overfitting, the neural network is not only trained on the plant dynamics but also on the plant disturbance. In order to deal with this, two methods can be used: training with a *regularization term* and *pruning* [4], [12]. Both methods are used in this paper. The regularization term α can be found in (6) and it is tuned to be as $\alpha = 10^{-3}$.

To implement these methods the *Neural Network Based System Identification TOOLBOX* [13] is used. It contains algorithms for the training and the validation of multilayer perceptron neural networks together with methods for pruning and the regularization term.

Using the data generated in the closed-loop, a NNARX model of the experimental neutralization plant is found. The result is a neural network which has $p = 11$ neurons, uses $n = 11$ past outputs as well as $m = 10$ past inputs and has a delay of $d = 1$. The number of past inputs m and past outputs n was determined with an order index criterion based on Liptschitz quotients [4]. The 10-step ahead prediction with the NNARX model in comparison to the validation signal can be seen in Figure 7. It has to be noted that the data set used to train the neural network and the data set used for validation are two different ones. Since the storage volume of the acid solution is limited the measurement period is also limited. This may reduce the quality of the nonlinear model; however, as shown in Figure 7 the plant behavior has been identified with satisfactory in the 10-step ahead prediction. In the following sections this neural network model is used for the APC controller as well as for tuning the controller in a simulation build-up.

IV. Approximate Predictive Control

The main concept behind common predictive control strategies is to predict the future outcome of different plant inputs and to choose the best out of these. Its calculations are relatively time consuming, this being its main disadvantage.

The minimization problem:

$$\min_{\tilde{U}_k} J_k = \min_{\tilde{U}_k}(\sum_{i=N_1}^{N_2}(r_{k+i} - \hat{y}_{k+i})^2 + \rho\sum_{j=1}^{N_u}\Delta u^2_{k+j-1}), \quad (7)$$

where J_k is the cost function, r_{k+i} is the known future reference signal and ρ is a factor which penalizes the influence of the input signals on the cost function has to be solved at each instant k. Moreover $\tilde{U}_k$ is a vector with the most recent control input changes given as:

$$\tilde{U}_k = [\Delta u_k \quad \Delta u_{k+1} \quad \ldots \quad \Delta u_{k+Nu-1}]^T, \quad (8)$$

where $\Delta = 1 - z^{-1}$ with z^{-1} is a time delay operator (i.e. $z^{-p}u_k = u_{k-p}$). At each instant only the first computed input change Δu_k is applied to the plant and then the whole computation is repeated for the next instant.

To solve this minimization problem the predicted outputs $\hat{y}_{k+i}$ within the fixed prediction horizon have to be determined. To reduce the calculation time requirements the *General Predictive Control* (GPC) approaches use a linear model to predict the future outputs [14], [15]. This results in a linear optimization problem with a new linear model for each sampling period. *Approximate Predictive Control* (APC) is a special case of the GPC approach, where the linear model is extracted from a neural network. This is known as *instantaneous linearization* [4]. In Figure 8 the block structure of the APC is shown.

A detailed introduction of the APC can be found in [4], and a toolkit which uses these formulas is implemented in [16].

V. Experimental Study

In this section the experimental results of the APC on the pH neutralization plant are presented. A set point tracking problem as well as a disturbance rejection problem are considered. It is difficult to adjust the parameter values of the controller directly in the real experimental plant because of its nonlinear behavior, the time intensive preparations to run the plant and the long measurement duration to obtain sufficient measurements. Therefore, first the parameter values of the APC are adjusted off-line with the neural network model identified earlier, then the APC is tried on the experimental plant.

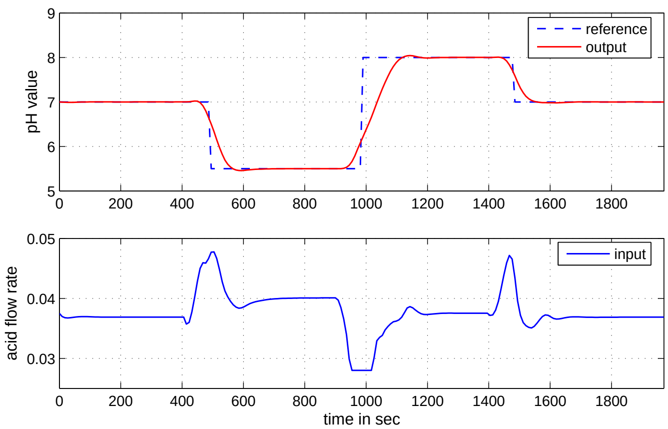

Fig. 9. Simulation results of a set point tracking problem with APC ($N1 = 1$, $N2 = 10$, $Nu = 2$ and $\rho = 2000$).

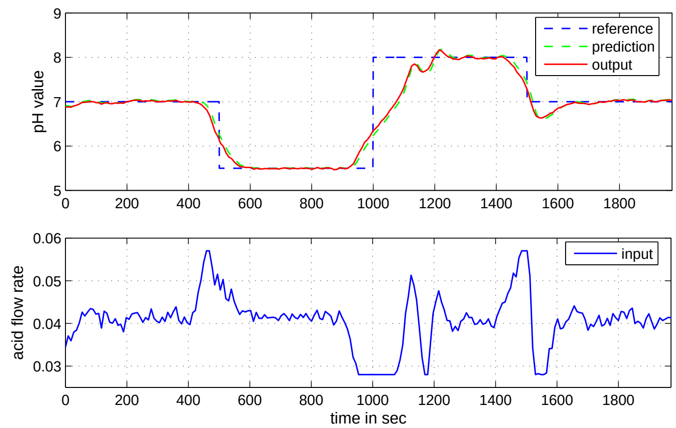

Fig. 10. Experimental results of a set point tracking problem with APC ($N1 = 1$, $N2 = 10$, $Nu = 2$ and $\rho = 20000$).

A. *Off-line parameter values adjustment*

The neural network model found in Section III-B which provides the results shown in Figure 7 is used to tune the APC off-line. The model is used twofold: first it is applied inside the APC structure (for this purpose the neural network model is constructed as shown in Figure 8), and second it simulates the plant that has to be controlled.

The parameter values of the APC are adjusted as follows: $N_1 = 1$ is fixed and equals the delay of the system. N_2 is selected as $\frac{t_r}{T_s} = 10$ so that the prediction horizon covers at least the rise time of the plant; $N_u = 2$ is chosen relatively small in comparison with N_2. It has been observed that the choice of N_2 and N_u is mostly unproblematic and gives good results for different values. The value of ρ in (7), which penalizes the control signal, should be carefully tuned. With $\rho = 2000$ a satisfactory tracking capability has been achieved in simulation.

Figure 9 shows the simulation results of the set point tracking problem. The reference signal is a three level signal that changes each 500 seconds. The APC produces reasonable control inputs and the output tracks the reference signal in a satisfactory manner. Finally, in Figure 9 the proactive characteristic of the APC can be observed because the control action begins earlier than the change in the reference. Next, the above parameter values are used with the real experimental plant.

B. *Experimental results*

The same obtained controller parameters have been utilized when the APC is tested on the real experimental pH neutralization plant. However, to improve the tracking capability and to reduce some oscillations which appear during the implementation, the value of ρ has been further tuned online, and it turns out that its best value is $\rho = 20000$.

The resulted measurement on the set point tracking problem is shown in Figure 10. The first change from pH-value 7 to 5.5 is unproblematic and relatively well done. The changes from pH 5.5 to 8 and then back to 7 are not ideal, but the control signal touches its limits, in particular, the lower one. Overall the results are reasonable and almost the same as the simulated ones.

From Figure 10 it can be also seen that the prediction is close to the real output, which shows that the model can capture the dynamics of the plant very well.

Finally the performance of the APC on a disturbance rejection problem is considered. The same parameter values as in the set point tracking problem are used. The task for the controller is to hold a constant pH-value equal 6, while some unmeasured disturbances are acting on the alkaline input stream. In Figure 11 the results are presented. The first disturbance is done by increasing the base valve opening for one sampling period from 0.2 to 0.4, which is equivalent to a three times higher alkaline flow rate. The second disturbance is obtained by reducing the valve opening from 0.2 to 0 for two sampling periods. It can be observed that the controller directly reacts with a change of the acid inflow when a deviation in the pH value occurs. Furthermore, it can be seen that the disturbance can not bring the pH-value far from the reference.

VI. Conclusion

In this work an approximate predictive control strategy for an experimental pH neutralization plant has been carried out. In closed-loop, with a multisine input signal, an identification data set has been gathered. A multilayer preceptron network with a NNARX model structure has been trained. Based on the trained neural network model, an APC has been off-line tuned and then implemented on the experimental plant.

The experimental results of a set point tracking and a disturbance rejection problems have demonstrated the capability of the APC to control the experimental pH neutralization plant successfully.

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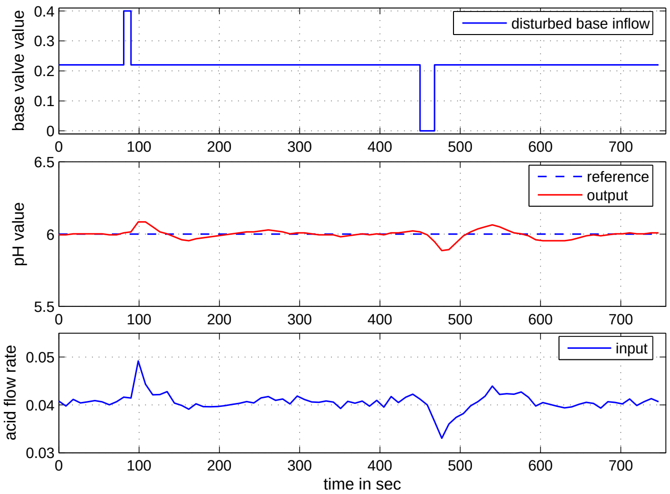

Fig. 11. Experimental results of a disturbance rejection problem with APC ($N1 = 1$, $N2 = 10$, $Nu = 2$ and $\rho = 20000$).

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