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ARTIFICIAL NEURAL NETWORK MODEL-BASED PREDICTIVE REAL-TIME CONTROL OF A CASCADED TWO TANK SYSTEM

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ABSTRACT

The development of reliable first principle models that totally describe the dynamic behaviour of nonlinear systems is a difficult and time-consuming task. This poses a major challenge in the development of nonlinear model-based controllers for industrial processes. Hence, an alternative approach which involves the use of artificial neural network (ANN) models for real-time predictive control of a cascaded two tank system housed in our laboratory is explored in this research work. To achieve this, the tank process was excited by well-designed input signals within a specified range to obtain real-time input-output data at a sampling time of 2s. The datasets obtained were used to fit recurrent neural network (RNN) and feedforward neural network (FFNN) models for the process. Thereafter, the models were used in the design of predictive controllers. The designed controllers were compiled and deployed to an Arduino microcontroller interfaced with the process to achieve real-time control. Validation results showed both models have good fits. The closed loop experimental results also showed good setpoint tracking performance for both controllers.

Keywords: Recurrent neural network, feedforward neural network, plant-model mismatch, Real-time control.

1. INTRODUCTION

Model predictive control (MPC) has become the advanced control method of choice in the process industries. This is largely because it has proven to be effective in handling processes which are somewhat difficult for classical controllers such as multivariable systems and systems which exhibit complex dynamics such as large time delays, non-minimum phase behaviour and input multiplicities.

Most industrial implementations of MPC utilize a linear model for prediction. Linear MPCs usually give satisfactory performance when it is desired to keep the controlled variable at a constant setpoint and the control problem is a regulatory one. For processes which are required to operate at different operating regimes or which the nonlinearities are very severe even in the neighbourhood of a single operating point, MPCs which make use of nonlinear prediction models give significantly better control performance (Bamidele, 2016).

The synthesis of a nonlinear model is however a crucial step in the design of any nonlinear model predictive control (NMPC) algorithm. Nonlinear models commonly used can be broadly classified either as first principle (white-box) models or empirical (black-box) models. First principle models give accurate predictions over the entire operating range of a system but development of these types of models is time-consuming and can be very difficult or impossible for some complex processes. In such cases, empirical modelling can be useful in that it requires no inherent knowledge of the system dynamics, given that sufficient input-output data is available.

Various types of empirical models which have been used in NMPC algorithms include Volterra models (Maner, 1996), polynomial autoregressive moving average model with exogenous inputs – polynomial ARMAX (Sriniwas and Arkun, 1997), Hammerstein and Weiner models (Chu and Seborg, 1994; Dumont et al., 1994), Weiner-Laguerre models (Mahmoodi et al., 2009) and artificial neural networks (Su and McAvoy, 1997). Amongst all the aforementioned empirical model types, artificial neural networks (ANN) have earned the reputation of being a powerful data-driven and flexible computational tool having the capability of capturing nonlinear and complex underlying characteristics of any process with a high degree of accuracy given that the input and output values of such a process have finite values. The use of ANNs for time series modelling and system identification is prevalent in the research community (Narendra and Parasarathy, 1990; 1992; Kuschewski, 1993). Based on architecture, neural networks can be broadly classified as either feedforward or recurrent. Both network types were utilized in this research work.

Despite the improved prediction capability associated with the use of highly accurate nonlinear empirical models, in real-life processes, plant-model mismatch arising from unmeasured disturbances, sensor noise, and/or unmodelled dynamics is an inevitable occurrence. This can cause severe degradation in the performance of a predictive controller. Though recurrent neural networks (RNN) possess an output error structure that can compensate for mismatches up to a certain extent, steady-state offsets have been observed to exist when feedforward neural network (FFNN) models are used in conventional MPC schemes. (Chu et al., 2003).

To combat this problem, several methods have been proposed. The most widely used approach is to update the model prediction using an output feedback error generated by comparing the predicted process output with the measured process output. The error term is assumed to be constant throughout the prediction horizon. Due to the fact that this technique was first implemented in the dynamic matrix control (DMC) algorithm, it is often called the "DMC-like offset correcting scheme". This scheme is however only capable of eliminating steady-state offsets in cases of mild plant-model mismatch (Tian et al., 2014; Sobowale, 2019).

Another simple yet novel approach to alleviate the mismatch problem is that proposed by Tian et al. This technique exhibits a high degree of robustness and has produced excellent results in some simulation studies (Tian et al., 2014; Sobowale, 2019). Further research (Sobowale, 2019) has however shown that it causes amplification of measurement noise leading to undesirable sustained oscillatory responses. This makes it quite unsuitable for real-time control. Plant-model mismatch problems in NMPC algorithms can also be tackled using a parameter adaptation technique (Huberman and Lumer, 1990; Al Seyab, 2006; Bamimore, 2016), an offset-correcting scheme which these researchers (Bamimore, 2016; Sobowale, 2019; Kehinde-Abajo, 2019) have shown to produce impressive setpoint tracking results in the presence of unmeasured disturbances, measurement noise and uncertainties in model parameters.

In this research paper, FFNN and RNN models were utilized in NMPC algorithms with parameter adaptation technique for the real-time control of a cascaded two-tank system. The rest of the paper is organized as follows: the theoretical framework is developed in section 2. The results and discussion of the servo problem are displayed in section 3 while the conclusions are given in section 4.

2. THEORETICAL FRAMEWORK

2.1. Problem Statement

Consider the laboratory scale cascaded two tank process, specifically designed by our group for process control studies. It has two level sensors, a DC pump and an electronically controlled valve. This system is interfaced with the computer via an Arduino micro controller board. The process is a 2×2 system having the pump flow rate and valve opening as manipulated variables and the heights of water in tanks 1 and 2 as the controlled variables. A simplified schematic of the process is shown in Figure 1. There are three different functional levels for this experimental system. The first level is known as the Plant and Field Instrument Layer, the second level is the Data Acquisition System Layer and the third level is the Supervisory Computer System Layer. The overall system architecture of the pilot plant is shown in Plate 1 of the Appendix.

The control problem in this process is to regulate the levels of water inside the two tanks at their setpoints using an ANN based NMPC controller.

Consider that the dynamics of water levels in the two tanks can be described by the nonlinear auto-regressive (NARX) model:

$$y_m(k+1) = f\big[y(k), \dots, y(k-n_y+1), u(k), \dots, u(k-n_u+1)\big] \quad (1)$$

were k stands for the sampling time, the function $f(.)$ represents m_y-dimensional nonlinear vector mapping of the plant's model, while $u(k) \in \mathbb{R}^{m_u}$, $y(k) \in \mathbb{R}^{m_y}$ and $y_m(k) \in \mathbb{R}^{m_y}$ are the plant's manipulated inputs and outputs, and model prediction respectively; whereas n_y and n_u refer to the maximum lags in the process output and input respectively.

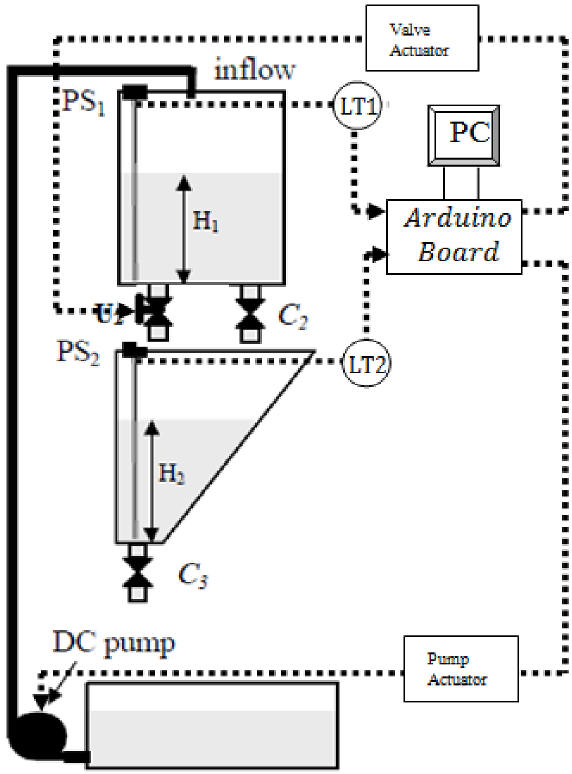

Figure 1: Experimental setup of cascaded two tank system

In this study, the model structures assumed for (1) are feedforward neural network (FFNN) and the recurrent neural network (RNN). Using historical input-output data of the plant, a one-step ahead FFNN can be trained to represent the plant model (1). Thus,

$$y_m(k+1) = \mathrm{W_o}[f_h\{\mathrm{W_I}\psi(\mathrm{k}) + \mathrm{b_I}\}] + \mathrm{b_o} \quad (2)$$

where

$$\psi(\mathrm{k}) = [y(k), \dots, y(k-n_y+1), u(k), \dots, u(k-n_u+1)];$$

$\mathrm{W_o}$ and $\mathrm{W_I}$ represent the output and input weights respectively; $\mathrm{b_o}$ and $\mathrm{b_I}$ represent the output and input biases respectively. The function $f_h(.)$ stands for the activation function for which the universal approximation theorem holds (Cybenko, 1989; Hornik, 1991), selected in this study as:

$$f_h(\mathrm{x}) = \frac{2}{(1+\mathrm{e}^{-2\mathrm{x}})} - 1 \quad (3)$$

By using Equation 2 recursively, the multi-step-ahead prediction can be obtained thus

$$y_m(k+i) = \mathrm{W_o}[f_h\{\mathrm{W_I}\psi(\mathrm{k+i-1}) + \mathrm{b_I}\}] + \mathrm{b_o} \quad (4)$$

Alternatively, an internally recurrent neural network called 'Elman' network can be trained to represent the plant model. Following the same procedure as above, a multistep-ahead prediction model is obtained as:

$$h(k+i) = f_h[W_I u(k+i-1) + W_L h(k+i-1) + b_I] \quad (5)$$

$$y_m(k+i) = W_o h(k+i) + b_o \quad (6)$$

where $h(k)$ is the output of the hidden layer and $\mathrm{W_L}$ stands for hidden layer weight.

2.2. NMPC problem formulation

The NMPC control problem is then formulated as finding the incremental inputs over the control horizon, i.e., $\Delta u(k+i), \ldots, \Delta u(k+N_c-1)$, which minimize the cost function:

$$J = \min\left\{\sum_{i=1}^{N_p}\|r(k+i) - y_m(k+i)\|_{w_y}^2 + \sum_{i=0}^{N_c-1}\|\Delta u(k+i)\|_{w_{\Delta u}}^2\right\} \quad (7a)$$

and subject to the constraints on process input rates, inputs and outputs:

$$\Delta u_{min} \leq \Delta u(k+i) \leq \Delta u_{max} \quad i = 0, \ldots, N_c - 1 \quad (7b)$$

$$u_{min} \leq u(k+i) \leq u_{max} \quad i = 0, \ldots, N_c - 1 \quad (7c)$$

$$y_{min} \leq y_m(k+i) \leq y_{max} \quad i = 1, \ldots, N_p \quad (7d)$$

where N_p and N_c are the prediction and control horizon respectively; w_y and $w_{\Delta u}$ are the output and input rate weighing matrices respectively; r is the setpoint trajectory.

3. METHODOLOGY

3.1. Data Collection and ANN models Identification

For the purpose of collecting data for ANN models identification, the two inputs (U_1 *and* U_2) to the experimental tank process were excited by random signals in the range [80 160] and [0.1 1] respectively. Switching time of 150s and 200s were used for inputs U_(1)and U_2, respectively, as these were the approximate settling times of the two levels. A low pass filter was used to reduce the effect of the noise during the data collection. 15000 input-output data set were collected at a sampling rate of 2 seconds. The 2 seconds sampling time was small enough to capture the nonlinearities in the data and prevent aliasing whilst offering a burden not too difficult for our computing systems to handle. Figure 2 shows a portion of the data samples obtained. After a series of trials and errors, the FFNN model was designed using a 8-10-10-2 configuration, that is, eight neurons in the input layer, 10 neurons in each of the two hidden layers and 2 neurons in the output layer. Further increment in neurons was observed not to result in any appreciable increase in model prediction accuracy. Using same procedure, the RNN was designed using a 2-8-2 configuration, that is, two neurons in the input layer, 8 neurons in the hidden layer and 2 neurons in the output layer. Less number of neurons was used in RNN because it usually requires fewer neurons to achieve an identical modelling accuracy as FFNN. The two networks were also trained using the Bayesian Regularization algorithm to minimize the Mean Square Error (MSE) between the predicted and actual outputs.

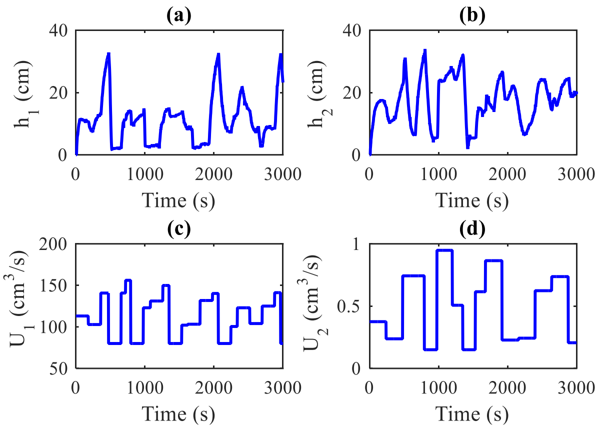

Figure 2: Input-Output data from the experimental system: (a) Height of tank 1 (h_1) (b) Height of tank 2 (h_2) (c) Pump flowrate (U_1) (d) Actuated valve opening (U_2)

4. RESULTS AND DISCUSSION

4.1. Trained ANN models validation results

For the purpose of ascertaining the fidelity of the trained ANN models, some fractions of the data collected during process identification were used for model validation. After model validation, the R^2 values obtained were 0.80258 and 0.80759 for the FFNN and RNN models, respectively. In addition, the MSE values obtained for the FFNN and RNN models are 25.4187 and 23.9598, respectively. These values revealed that the identified models have good fits. They also showed that the two identified ANN models have a comparable performance and accurate enough for predictive controller design.

4.2. Closed-loop experimental results

The trained ANN models were later used for predictive controllers design. The designed predictive controllers were deployed for the control of the cascaded-tank process in real-time. The servo performance of the designed controllers were observed and evaluated after introduction of the following setpoint changes depicted in Eqns (8a) and (b). Graphical presentations of variations of the controlled and manipulated variables with time for the $FFNN$ and RNN model based predictive controllers are shown in Figures 3 and 4 respectively.

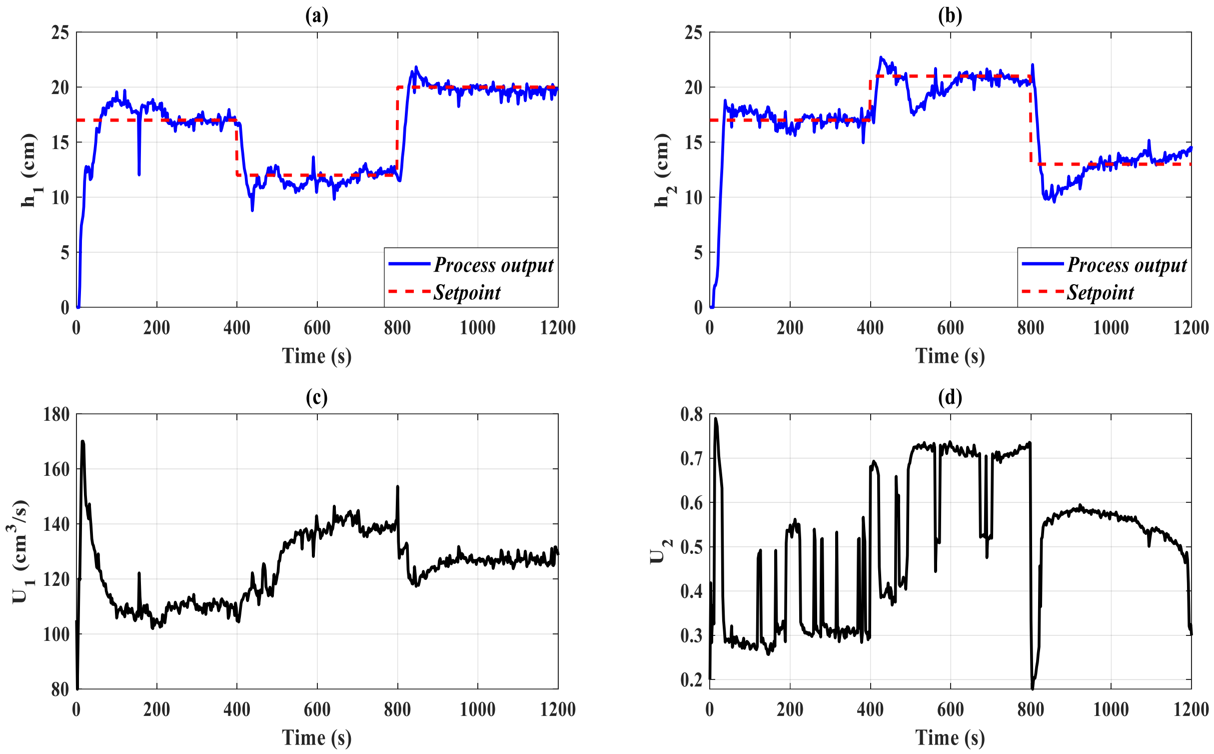

***Figure 1.3**: Evolution of controlled and manipulated variables with time $(FFNN - NMPC)$: Height of tank 1 (h_1) (b) Height of tank 2 (h_2) (c) Pump flowrate (U_1) (d) Actuated valve opening (U_2)*

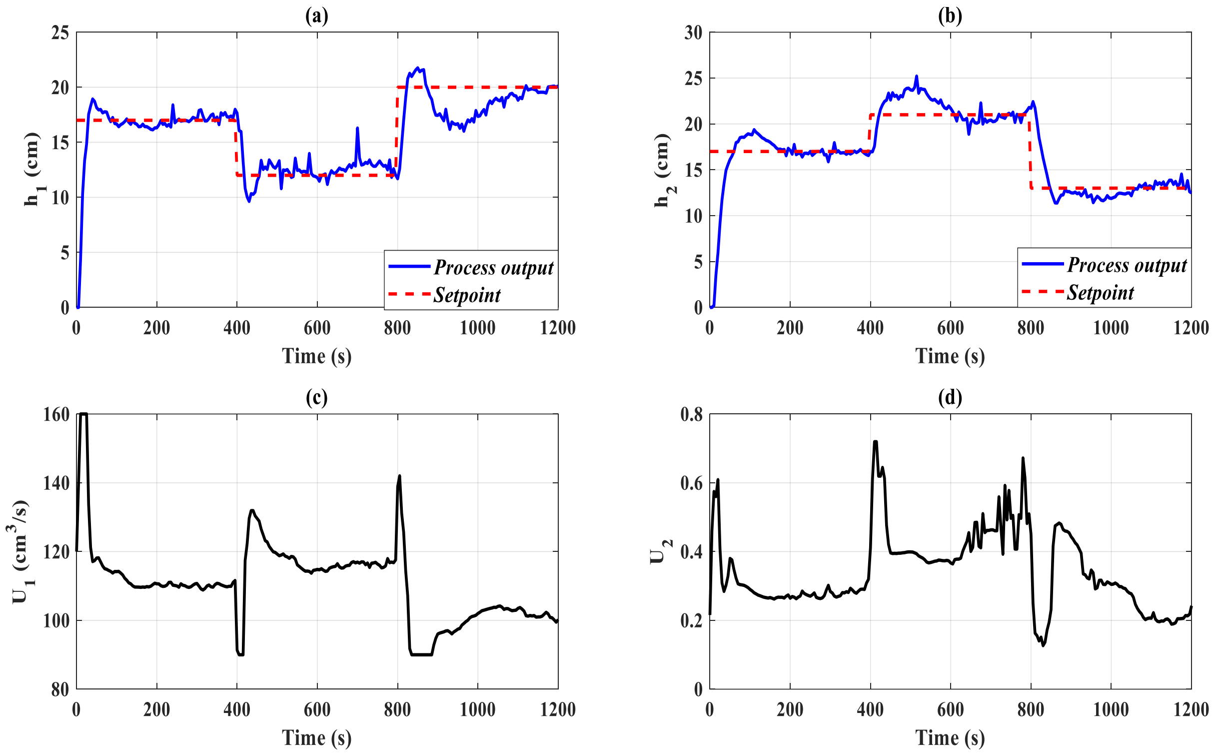

Figure 1.4: Evolution of controlled and manipulated variables with time $(RNN - NMPC)$: Height of tank 1 (h_1) (b) Height of tank 2 (h_2) (c) Pump flowrate (U_1) (d) Actuated valve opening (U_2)

$$h_{1_{set}} = \begin{cases} 17, & 0 \le t \le 400 \\ 12, & 400 < t \le 800 \\ 20, & 800 < t \le 1200 \end{cases} \qquad (8a)$$

$$h_{2_{set}} = \begin{cases} 17, & 0 \le t \le 400 \\ 21, & 400 < t \le 800 \\ 13, & 800 < t \le 1200 \end{cases} \qquad (8b)$$

These results revealed that both FFNN-NMPC and RNN-NMPC give good and comparable set-point tracking with small overshoots and undershoots. However, the control signal u_2 in FFNN-NMPC is a little noisy which is due to small weight used on u_2.

The integral absolute error (IAE) between the process outputs and setpoints which serves as a criterion for assessment of controller performance is summarized in Table 1. These showed FFNN-NMPC having slightly lower IAE values than RNN-NMPC. The NMPC tuning parameters are summarized in Table 2.

Table 1: IAE values in setpoint tracking for both controllers

	$h_{1_{set}} - h_1$	$h_{2_{set}} - h_2$
$FFNN\text{-}NMPC$	1239.5	1459.9
$RNN\text{-}NMPC$	1477.0	1635.9

Table 2: Predictive Controllers tuning parameters

	FFNN-NMPC	RNN-NMPC
Sampling time (s)	2	2
Prediction horizon (N_p)	20	20
Control horizon (N_u)	1	2
Input U_1 [min, max] (cm^3/s)	$[80, 170]$	$[80,170]$
Input U_2 [min, max]	$[0.1, 1.0]$	$[0.1, 1.0]$
Input rate (ΔU_1) [min, max]	$[-20, 20]$	$[-20, 20]$
Input rate (ΔU_2) [min, max]	$[-0.4, 0.4$	$[-0.1, 0.1]$
Output h_1 [min, max]	$[0, 30]$	$[0, 30]$
Output h_2 [min, max]	$[0, 30]$	$[0, 30]$
Weights		
Output W_y	diag(10, 10)	diag[100,100]
Input rate $W_{\Delta u}$	diag(0.001, 0.06)]	diag[0.5, 200]

5. CONCLUSION

In this research work, two types of artificial neural network models, namely feedforward and recurrent neural networks models have been identified to describe the dynamic behaviour of the cascaded two tanks process using real-life input-output data collected from the tank. Thereafter, Nonlinear model predictive controller were designed from the identified ANN models and used for the direct digital control of the tank in real-time. Parameter adaptation method was used to handle the issue of plant-model mismatch in the tank's levels responses.

As shown by the results of validation experiment, both FFNN and RNN show great potentials in modelling dynamic systems. Also, as observed in the good set-point tracking results obtained from real-time implementation on the cascaded two tank system, both FFNN-NMPC and RNN-NMPC will find application in the process industries where plant's history data are available and it is expensive in building a model from first principle.

It is hope that the newly designed cascaded two-tank process will be used extensively for research and educational training purposes of both undergraduate and post-graduate students in the area of process systems engineering.

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Appendix

Plate 1: Experimental Setup of cascaded two tank system

Dynamic models of the tank system

The dynamics of the levels of water inside the two tanks are described by the first principle models:

$$\dot{h_1} = \frac{1}{aw}\left(U_1 - U_2 S_p\sqrt{2gh_1} - C_2 S_p\sqrt{2gh_1}\right)$$

$$\dot{h_2} = \frac{H}{bwh_2 + cwH}\left(U_2 S_p\sqrt{2gh_1} - C_2 S_p\sqrt{2gh_1} - C_3 S_p\sqrt{2gh_2}\right)$$

Model Parameters

$w = 3.5cm, a = 25cm, b = 34.5cm,\ S_p = 1.267cm^2, H = 35cm,$ $g = 981cm^2s^{-1}$,

$C_2 = 0.4347, C_3 = 0.7347$

Nominal Operating Points

$U_1 = 170cm^3s^{-1}, U_2 = 0.3, h_1 = 17cm, h_2 = 17cm$

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