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Predictive Controller Design for catalytic Continuous Stirred Tank Reactor using Machine Learning

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ABSTRACT: In catalytic Continuous Stirred Tank Reactor (CSTR), the use of Model Predictive Control (MPC) increases the output power. However, MPC has the disadvantage of a high computational demand that hinders its application to some processes. In this paper, a predictive control strategy is presented to mitigate all ramifications of the model's uncertainties and parameter mismatch between the plant and controller for the control of catalytic Continuous Stirred Tank Reactor (CSTR) plant. A specific neural network structure is proposed as a model-free current predictive control for the plant.After the training process, the proposed neural network combined with the predictive controller using a performance criterion overcomes parameter variations in the physical system. The results show that the neural network controllers provide practically the same mean power as the MPC controller with differences under 0.02 kW for most neural networks, less abrupt changes at the output and slight violations of the constraints. Moreover, the proposed neural networks perform well, even using a low number of sensors and predictions, decreasing the number of neural network inputs to 10% of the original size.

KEYWORDS: Predictive control system, Neural Network, Feed-Back loop, State Estimation, close loop system.

I. INTRODUCTION

Many control algorithms have been proposed for catalytic Continuous Stirred Tank Reactor (CSTR) system, gathered in Refs. [1-5]. Among them, Model Predictive Control (MPC) [6] is widely used in the literature because it can deal with nonlinear behaviors and constraints, and the use of receding horizon allows it to take into account future outputs. More details of the control techniques applied to catalytic Continuous Stirred Tank Reactor (CSTR) plants can be found in section [7-10].

The main drawback of MPC is the high computational cost required to solve an optimization problem every few minutes or seconds. This paper proposes the use of Artificial Neural Networks (ANN) to overcome this drawback. There are two main approaches to the application of neural networks to control systems:

The most commonly used approach consists of using the ANN to model the behavior of the plant [7] gathers a list of applications to various industrial plants and, more specifically, some applications to catalytic Continuous Stirred Tank Reactor (CSTR). In Ref. [8], a Nonlinear Autoregressive Exogenous (NARX) neural network is applied to obtain a non-linear model of the plant [9]. Authors have used an Elman neural network to tune offline switching PIDs and in Ref. [10], an MPC controller is applied using a state-space neural network as a model. In Ref. [11] a neural network is used to estimate the optimal operating point in a real-time optimization scheme for catalytic Continuous Stirred Tank Reactor (CSTR).

The second approach is to calculate the control signal directly. To the best of our knowledge, it has not been applied to catalytic Continuous Stirred Tank Reactor (CSTR), but there are some applications in other fields [12]. Approximate the output of a receding horizon controller using feedforward neural networksapplied to control the trajectory of a robot [13]. Use a neuralnetwork to solve the optimization problem in MPC [14]. Learnto approximate the output of an MPC controller applied to anenergy management system in a smart building.

The main contribution of this work is to apply neural networksto directly approximate the output of a nonlinear MPC controller forthe control of parabolic trough collector fields. The proposedmethod provides control signals that approach the

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strengths ofMPC such as optimality and compliance with constraints, butwith much faster implementation times. In most controllers, one ofthe control objectives is to smooth the control signal and reduce theslew rate, which increases the pump durability, lowers high frequencynoise and reduces failures in electronic systems. A minorcontribution is to obtain less abrupt changes in the controlsignal. The whole process can be divided into three main steps: First, anMPC controller is implemented to generate a dataset. Then, severalartificial neural networks are trained offline to learn its outputs.Finally, the proposed NN controller is tested by simulation for thecatalytic Continuous Stirred Tank Reactor (CSTR) plant.

II. METHODOLOGY

The neural network predictive controller that is implemented in the Deep Learning Toolbox™ software uses a neural network model of a nonlinear catalytic Continuous Stirred Tank Reactor (CSTR) plant to predict future plant performance. The controller then calculates the control input that will optimize plant performance over a specified future time horizon. The first step in model predictive control is to determine the neural network plant model (system identification). Next, the plant model is used by the controller to predict future performance.

2.1 Predictive Control

The model predictive control method is based on the receding horizon technique [SoHa96]. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 +$$

$$\rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2$$

Where, N_1, N_2, and N_u define the horizons over which the tracking error and the control increments are evaluated. The u′ variable is the tentative control signal, y_r is the desired response, and y_m is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

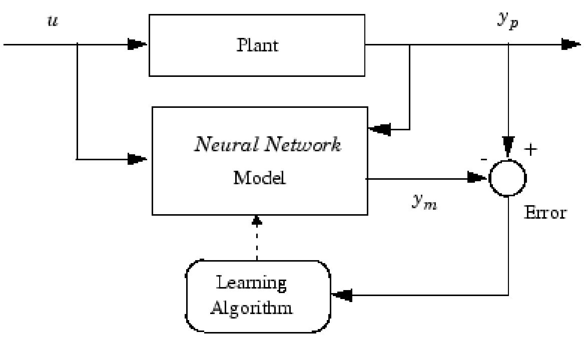

Fig. 1: The block diagram of model predictive control process.

The block diagram in fig. 1 illustrates the model predictive control process. The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of u′ that minimize J, and then the optimal u is input to the plant. The controller block is implemented in Simulink, as described in the following section.

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2.2 CSTR plant Description

This section shows how the NN Predictive Controller block is used. The first step is to copy the NN Predictive Controller block from the Deep Learning Toolbox block library to the Simulink Editor. This step is skipped in the following example.

An example model is provided with the Deep Learning Toolbox software to show the use of the predictive controller. This example uses a catalytic Continuous Stirred Tank Reactor (CSTR). A diagram of the process is shown in the fig. 2.

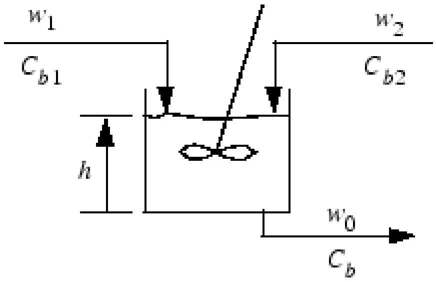

Fig. 2: catalytic Continuous Stirred Tank Reactor (CSTR).

The dynamic model of the system is

$$\frac{dC_b(t)}{dt} = (C_{b1} - C_b(t))\frac{w_1(t)}{h(t)} +$$

$$(C_{b2} - C_b(t))\frac{w_2(t)}{h(t)} - \frac{k_1 C_b(t)}{(1 + k_2 C_b(t))^2}$$

Where h(t) is the liquid level, $C_b(t)$ is the product concentration at the output of the process, $w_1(t)$ is the flow rate of the concentrated feed C_{b1}, and $w_2(t)$ is the flow rate of the diluted feed C_{b2}. The input concentrations are set to $C_{b1} = 24.9$ and $C_{b2} = 0.1$. The constants associated with the rate of consumption are $k_1 = 1$ and $k_2 = 1$.

The objective of the controller is to maintain the product concentration by adjusting the flow w1(t). To simplify the example, set w2(t) = 0.1. The level of the tank h(t) is not controlled for this experiment.

The Plant block contains the Simulink CSTR plant model. The NN Predictive Controller block signals are connected as follows:

❖Control Signal is connected to the input of the Plant model.
❖The Plant Output signal is connected to the Plant block output.
❖The Reference is connected to the Random Reference signal.

2.3 Developing Neural Network Algorithm

After trying both Fitting and NARX neural networks with various sets of input data, we determine that the NARX network works well for near-term predictions and the Fitting network is effective for both near- and long-term predictions. Data inputs to the neural networks include historical and forecasted wind, measured tide levels, and forecasted astronomical tide levels. We design and test the neural networks using the Neural Net Fitting and Neural Net Time Series apps built into Neural Network Toolbox. In matlab inputDelays = 1:24; feedbackDelays = 1:24; hiddenLayerSize = 7; net =

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narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn); commands are used to generate the required neural network. Fig 3 represents the neural network with 7 hidden layers.

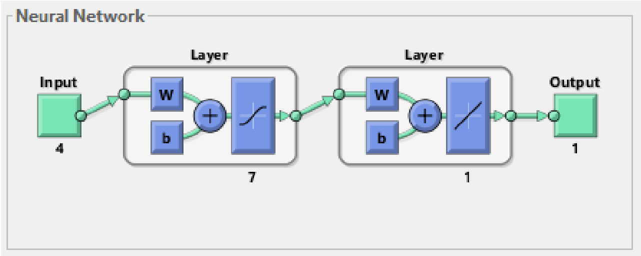

Fig. 3: Structure of proposed neural network.

III. SIMULATION RESULTS

In this section, we have discussed the various simulation result obtained from the Matlab simulation of the proposed scheme.

3.1 Training Data Generation

The performance of any neural network is based on efficiency of its training phase. For proper training of a neural network, a huge amount of training data is required. In this work, we have simulated the catalytic Continuous Stirred Tank Reactor (CSTR) plant in Matlab environment and training data is generated synthetically using Matlab Simulation. Fig. 3 shows the training data generated for input and output process of the catalytic Continuous Stirred Tank Reactor (CSTR) plant.

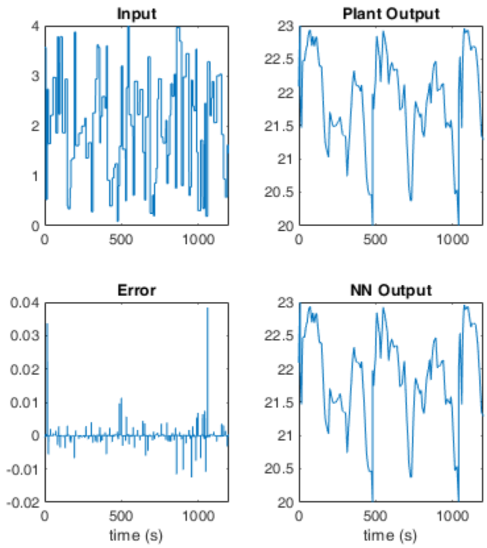

Fig. 3: Plant input output data for training of the neural network.

3.2Training performance

Fig. 4 represents the training performance of the proposed neural network algorithm. Here, we have chosen a network having 9 hidden layers. Here from fig.4 we can infer that the proposed neural network, gives minimum mean square error

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on training data and the maximum mean square error that we are getting is for Test data but in either case the mean square error is less than 0.01 which is a good performance.

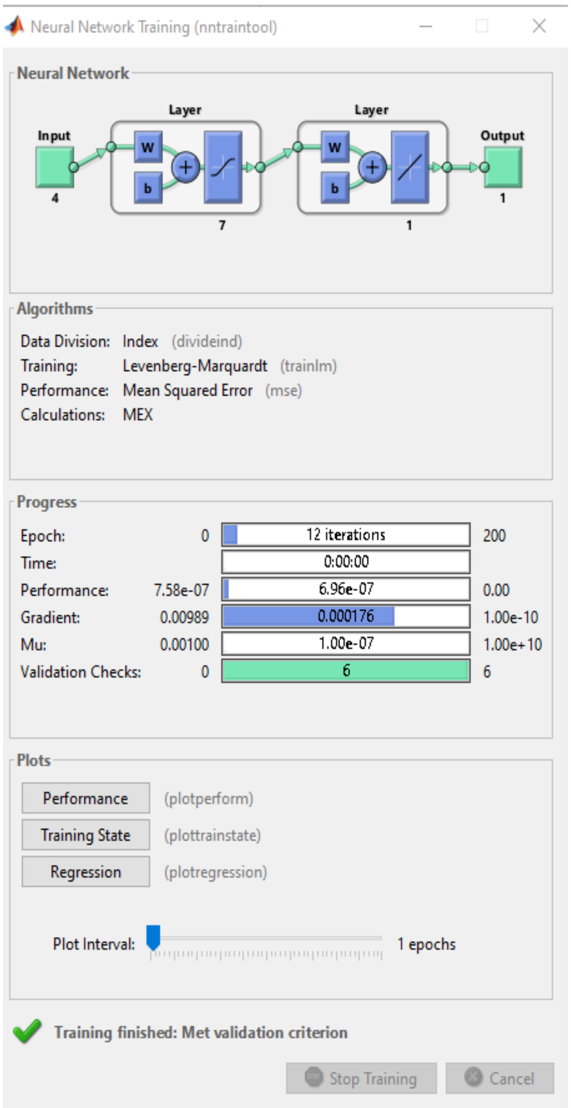

Fig. 4: Training process of proposed neural network based predictive control scheme.

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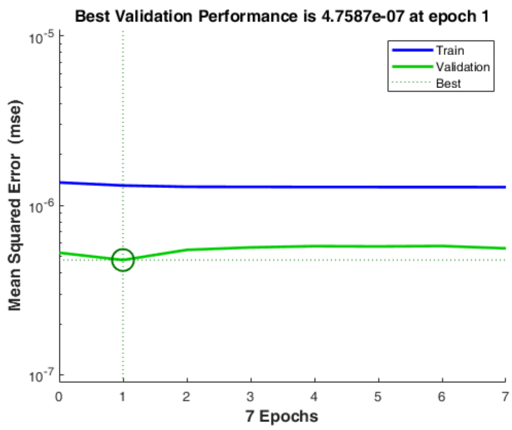

Fig. 5: Training performance of the proposed neural network.

3.3 Output Performance

Closed-loop simulation study is carried out to demonstrate the performance of the proposed estimation approach in the catalytic Continuous Stirred Tank Reactor (CSTR). The closed-loop simulations results using the NN based estimator are shown in Fig. 6. It can be seen from these figures that starting from different initial conditions and different initial estimates, the closed-loop states are stabilized at the steady-state under LMPC using NN-based state estimator.

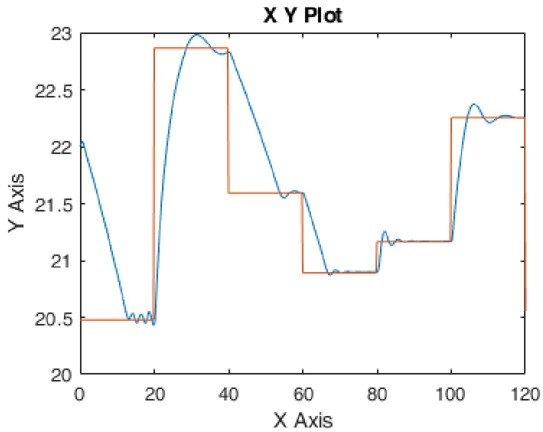

Fig. 6: Input-Output Transient Response of the system

In comparison with PID control, the settling time was reduced in about 33 %, and the overall consumption of hot medium was reduced in approximately 5 %.

IV. CONCLUSION

In this work, we proposed a machine-learning-based state estimation approach for nonlinear processes in catalytic Continuous Stirred Tank Reactor (CSTR) plant. The neural network model was first developed to represent process dynamics in the operating region. Then, the NN-based estimator was used to provide state estimates for the optimization problem of LMPC. From closed-loop simulations, it was demonstrated that NN- based estimator achieved a desired accuracy in state estimation, and all these trajectories initiating from different initial conditions converged to the steady state under the LMPC using NN-based estimator.

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