NEURO – FUZZY INTERNAL MODEL CONTROL

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Abstract

In this paper a robust predictive neuro-fuzzy control method for a nonlinear plant is addressed, proposed and tested. A neuro-fuzzy model is used to identify the process and then provides predictions about the process behavior, based on control actions applied to the system. The paper is consisting of theoretical and practical parts offers a neuro-fuzzy internal model control (NFIMC) design and its successful application. The structure of NFIMC is described in detail. The proposed control algorithm is applied for control the concentration in the chemical reactor by manipulating its flow rate.

1 Introduction

Nowadays, PID algorithms are used to control a majority of processes in industrial facilities. The proportional-integral-derivative (PID) algorithm is both simple and reliable, and has been applied to hundreds or even thousands of control loops in various industrial applications over the last 60 years. However, not all industrial processes can be controlled with conventional PID algorithms. Multivariable and highly nonlinear processes require more advanced control structures based on robust and soft techniques. Currently, many vendors have incorporated new advanced algorithms based on fuzzy logic and neural networks into their program systems. This new program system allows users to apply fuzzy logic and neural network algorithms to existing control structures and control loops. The main aim is to achieve a faster and tighter process response than with conventional PID techniques.

The neuro-fuzzy approaches use in model based predictive control an efficient tool for handling plants with complex dynamics as well as unstable inverse systems, time-varying time delay, occasional open-loop instability, plant model miss-matches, different uncertainties especially of complex non-linear systems.

The Internal Model Control (IMC) structure was firstly presented by Garcia and Morari [3]. Some of mentioned problem can be solved by implementing soft computing methods comprising the advantages of high approximation qualities of fuzzy logic and moreover learning capabilities of neural networks. The scientific research in model predictive control schemes applications with the help of artificial intelligence shows in the last decade very efficient results [2].

The paper is organized as follows. First, design of NFIMC is briefly introduced in Section 2. Then, the case study and simulation results are discussed in Section 3. Summary and conclusions are given in Section 4.

2 Internal Model Control using Neuro-Fuzzy Models

In process control, IMC has gained high popularity due to the good disturbance rejection capabilities and robustness properties of the IMC structure. The IMC is very often used in control strategies for linear systems and can be used for nonlinear systems as well. Structure of IMC is shown in Fig. 1. This structure allows the error feedback to reflect the effect of disturbance. It can be shown that a good match between forward and inverse models is enough to have good control and influence of disturbance is also reduces. IMC structure [1] with detail of the implementation is shown in Fig. 2.

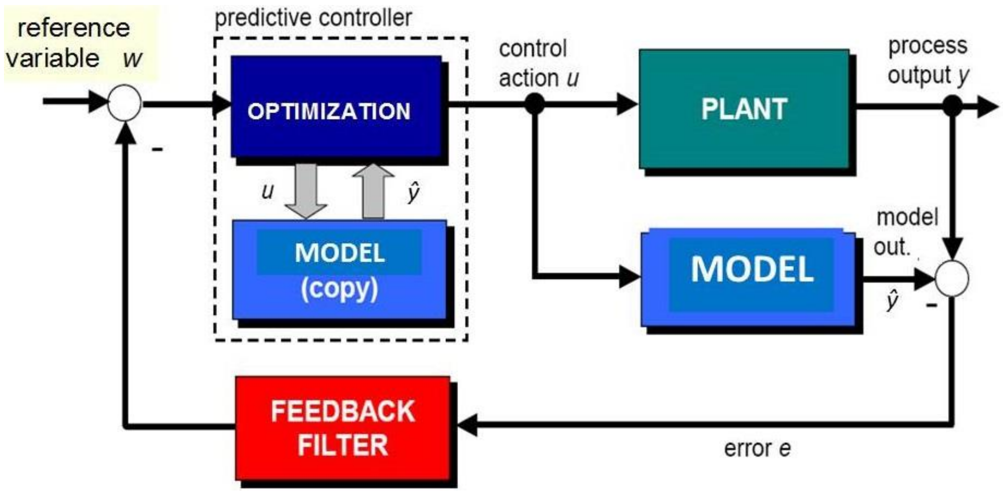

Figure 1: Block scheme of IMC

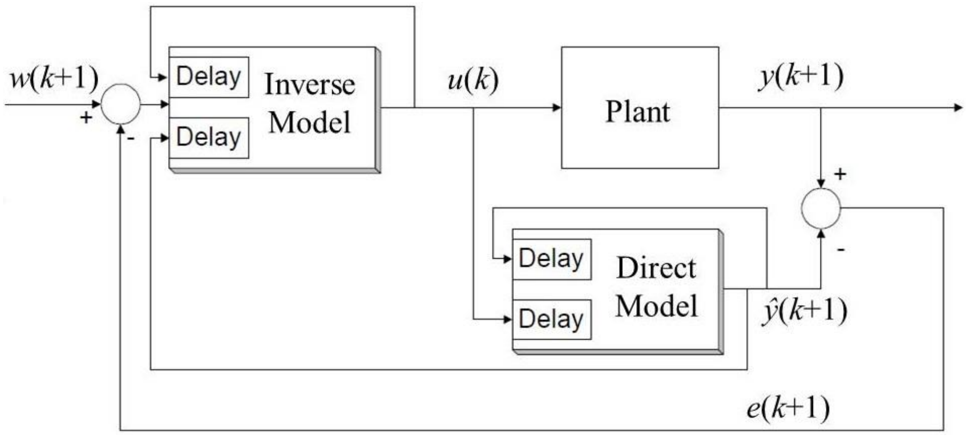

Figure 2: IMC structure with detail of the implementation of inverse and direct models – $w(k+1)$ is reference input signal, $e(k+1)$ is error between the output and the estimate, $u(k)$ is input signal to the plant, $y(k+1)$ is plant output, $\hat{y}(k+1)$ is the estimate of the output

The IMC and the classical feedback control can generate the same loop characteristics. The process model plays explicit role in the control structure compared to the standard control loop. The IMC structure has some advantages over conventional feedback control loops. If the process is stable, which is true for most industrial processes, the closed loop will be stable for any stable controller. The controller can simply be designed as a feed-forward controller in the IMC scheme.

Since the controller can be designed as an open-loop controller, the ideal choice for the controller is the inverse of the process model. The IMC design procedure is very simple and reliable. The direct model of the controlled process is Takagi-Sugeno (T-S) fuzzy model, membership functions are built on the triangular distribution curve. Design of the fuzzy model has been proposed from input-output measurement data. Still, compared to other nonlinear techniques, fuzzy models provide a more transparent representation of the identified model.

Parameters of the fuzzy model are adapted by neural network. The neuro-fuzzy model, which is obtained, has a very high accuracy. Main goal of this approach is to implement the predictive model-based control theory, advanced of neuro-fuzzy modeling technique to obtain a model with high accuracy and apply the possibilities of the inverse model-based fuzzy control.

First process outputs are changed with inputs and the same neuro-fuzzy algorithm is used for the obtaining of the inverse model. In the internal model-based scheme the quality of the designed neuro-fuzzy logic controller depends on the accuracy of the inverted neuro-fuzzy model presented by checking error. The inverse model of the controlled process is Takagi-Sugeno fuzzy model, which is created by using of fuzzy clustering algorithm.

3 Case Study and Simulation Results

The application considered involves an isothermal reactor in which the Van Vusse reaction kinetic scheme is carried out. In the following analysis, A is the educt, B the desired product, C and D are unwanted byproducts, see [4]

$$
\begin{aligned}
&A \xrightarrow{k_1} B \xrightarrow{k_2} C \\
&2A \xrightarrow{k_3} D
\end{aligned}
\tag{1}
$$

From a design perspective the objective is to make k_2 and k_3 small in comparison to k_1 by appropriate choice of catalyst and reaction conditions. The concentration of B in the product may be controlled by manipulating of the inlet flow rate and/or the reaction temperature.

The educt flow contains only cyclopentadiene in low concentration, C_{Af}. Assuming constant density and an ideal residence time distribution within the reactor, the mass balance equations for the relevant concentrations of cyclopentadiene and of the desired product cyclopentanol, C_A and C_B, are as follows:

$$
\begin{aligned}
&\dot{C}_A = -k_1 C_A - k_3 C_A^2 + \frac{F}{V}(C_{Af} - C_A) \\
&\dot{C}_B = k_1 C_A - k_2 C_B - \frac{F}{V} C_B \\
&y = C_B
\end{aligned}
\tag{2}
$$

This example has been considered by a number of researchers as a benchmark problem for evaluating nonlinear process control algorithm. Kinetic parameters of the chemical reactor are given in Table 1.

Table 1: KINETIC PARAMETERS

k_1	50 h^{-1}
k_2	100 h^{-1}
k_3	10 l mol^{-1} h^{-1}
C_{Af}	10 mol l^{-1}
V	1 l

This example has been considered by a number of researchers as a benchmark problem for evaluating nonlinear process control algorithm. By normalizing the process variables around the following operating point and substituting the values for the physical constants (Table 1), the process model becomes:

$$
\begin{aligned}
&\dot{x}_1(t) = -50x_1(t) - 10x_1^2(t) + u(10 - x_1(t)) \\
&\dot{x}_2(t) = 50x_1(t) - 100x_2(t) + u(-x_2(t)) \\
&y(t) = x_2(t)
\end{aligned}
\tag{3}
$$

where the deviation variable for the concentration of component A is denoted by x_1, the concentration of component B by x_2, and the inlet flow rate by u.

We have designed direct T-S fuzzy model for three operating points. The direct model has three Triangular membership functions for all two inputs $y(k\text{-}1)$ $u(k)$ and output is y(k). Then the inverse neuro-fuzzy model with subtractive clustering method was created. The inverse model has three inputs $u(k\text{-}1)$, $w(k\text{+}1)$, $y(k\text{-}1)$ and output is $u(k)$. The rules of both neuro-fuzzy models were created automatically in anfiseditor.

The comparison of time responses of output of direct neuro-fuzzy model with nonlinear plant is shown in Fig. 3. Time responses of the controlled and reference variables under NFIMC are shown in Fig. 4. Time responses of manipulated variable under NFIMC are shown in Fig. 5.

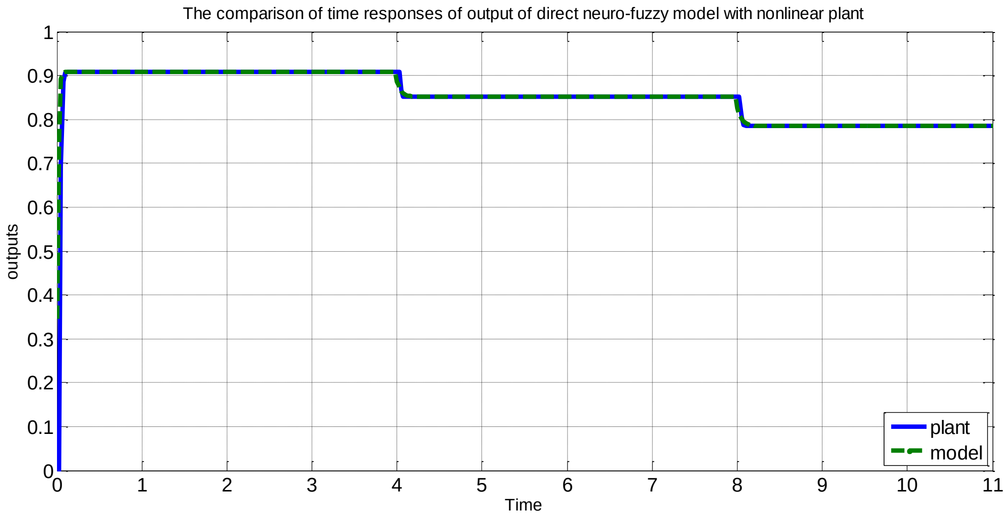

Figure 3: The comparison of time responses of output of direct neuro-fuzzy model with nonlinear plant

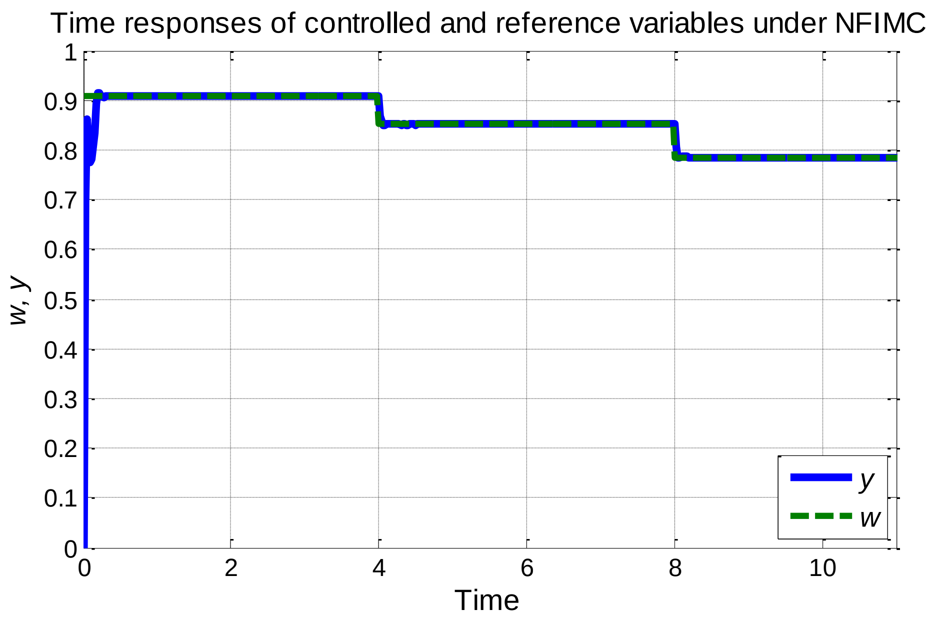

Figure 4: Time responses of the controlled and reference variables of the process under NFIMC

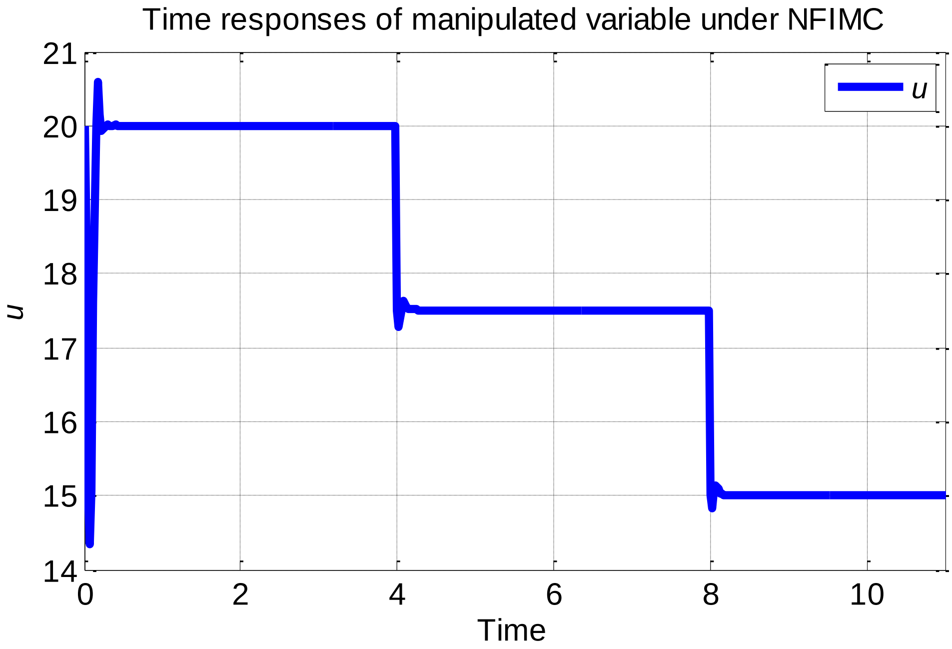

Figure 5: Time response of the manipulated variable under NFIMC

4 CONCLUSION

In this paper NFIMC for control of nonlinear process are designed. The performance of control is dependent on many factors. FNIMC is very effective method, which is based on neuro-fuzzy model and the existing of inverse neuro-fuzzy model. The performance of FNIMC depends on the accuracy of neuro-fuzzy model.

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References

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