2017 21st International Conference on Process Control (PC)
June 6–9, 2017, Štrbské Pleso, Slovakia

Internal Model Control of Thermo-Optical Plant

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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 consists of theoretical and practical section, offers an internal model control and a neuro-fuzzy internal model control designs and their successful application. The structure of both of algorithms is described in detail. The proposed control algorithms are applied to control of a thermo-optical plant.**

Keywords—fuzzy models; internal model control; neural networks; nonlinear models

I. Introduction

In practice, proportional-integral-derivative (PID) algorithms are applied to control of a huge amount of industrial facilities. The conventional PID technique is both reliable and simple, it has been used to hundreds of thousands of control loops in various industrial facilities all over the world in the last 70 years. In spite of many advantages of using PID controllers, not all industrial processes can be controlled with conventional algorithms. Highly nonlinear processes or multivariable systems require more advanced control algorithms based on soft and robust strategies. Currently, majority of vendors have incorporated new advanced structures based on soft techniques into their control systems. This allows users to apply fuzzy logic, neural network algorithms and genetic algorithms to existing control loops and control structures. The main aim is to achieve better control loop performance compared to conventional PID algorithms.

Application of neuro-fuzzy approaches in model based predictive control is an effective tool for control of systems with complex dynamics as well as unstable inverse systems, time-varying time delay, occasional open-loop instability, plant model miss-matches and different uncertainties especially of complex nonlinear systems [2], [13].

The Internal Model Control (IMC) structure was firstly presented by Garcia and Morari [14]. Some of the mentioned problems can be solved by implementation of 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 very efficient results in the last decade. Application of adaptive fuzzy IMC is described in [3]. Neural network based control structure is given in [4] and [9]. Design of predictive controller based on fuzzy logic and neural network is presented in [8], [11] and [12].

The paper is organized as follows. First, design of IMC and neuro-fuzzy IMC (NFIMC) is briefly introduced in Section 2. Neuro-Fuzzy model is described in Section 3. Then, case study and simulation results are discussed in Section 4. Summary and conclusions are given in Section 5.

II. Control Structure

A. Internal Model Control Structure

In process control, IMC has obtained huge success due to the good disturbance elimination facilities and IMC structure robustness capabilities [5]. IMC techniques belong to a family of very simple, robust and easy-to-implement methods, suitable for many industrial applications. The IMC is very often used in control strategies for linear systems with the possibility of use for nonlinear systems as well. Structure of IMC is shown in Fig. 1. This structure provides the feedback error to yield the effect of disturbance. It can be shown, that a perfect match between forward and inverse models is enough to achieve acceptable control, while influence of disturbances is also reduced.

According to Fig. 1, the following relationship between the conventional feedback control $G_R(s)$ and internal model (predictive) controller $G_{RIMC}(s)$ can be seen

$$G_R(s) = \frac{G_{RIMC}(s)}{1 - G_{RIMC}(s)\hat{G}(s)} \tag{1}$$

and

$$G_{RIMC}(s) = \frac{G_R(s)}{1 + G_R(s)\hat{G}(s)} \tag{2}$$

The control variable can be expressed

$$U(s) = \frac{G_{RIMC}(s)}{1 - G_{RIMC}(s)(G(s) - \hat{G}(s))} W(s) \tag{3}$$

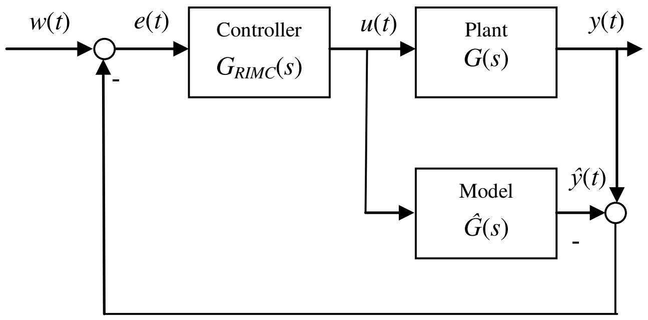

Fig. 1. Block Scheme of Internal Model Control.

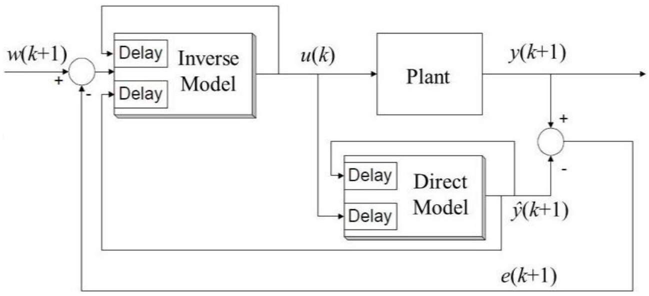

Fig. 2. Internal Model Control structure with detail of the implementation of inverse and direct models – $w(k+1)$ is reference input signal, $e(k+1)$ is error between the output and the estimate, $u(k)$ is input signal to the plant, $y(k+1)$ is plant output, $\hat{y}(k+1)$ is the estimate of the output.

Output variable is

$$Y(s) = \frac{G_{RIMC}(s)G_R(s)}{1 - G_{RIMC}(s)(G(s) - \hat{G}(s))} W(s) \tag{4}$$

From the derived relations, the following characteristics of the IMC control structures can be established:

- if the model is perfect and $G(s)=\hat{G}(s)$ then from (3) and (4) it is simple to find $U(s)=G_{RIMC}(s)W(s)$ and $Y(s)=\hat{G}(s)G_{RIMC}(s)W(s)$,
- stability condition of closed-loop systems: controller output will be bounded, if $G_{RIMC}(s)$ is stable. The output will be stable if plant and $G_{RIMC}(s)$ is also stable,
- the IMC structure provides perfect control for all time responses and all disturbances.

In implementation of IMC scheme, the following practical issues are assumed:

- the process model may be separable into invertible $\hat{G}^-$ and noninvertible part $\hat{G}^+$ (unstable poles, time delays, etc.) with the steady state gain $\hat{G}(s)= \hat{G}^+\hat{G}^-$
- the IMC controller is expressed as follows

$$G_{RIMC}(s) = \frac{1}{\hat{G}^-} G_{Y/W}(s) \tag{5}$$

$G_{Y/W}(s)$ is transfer function of closed-loop

$$G_{Y/W}(s) = \frac{1}{(\lambda s + 1)^n} \tag{6}$$

where the parameters λ and the order n are chosen to ensure that the $G_{RIMC}(s)$ is proper. Parameter λ determines dynamical properties of closed-loop system.

B. Neuro-Fuzzy Internal Model Control Structure

IMC structure with detail [10] of the implementation is shown in Fig. 2.

In order to increase the robustness and disturbance rejection performance of the modified IMC scheme, an adaptation mechanism is introduced on the neuro-fuzzy model.

This approach includes following parts:

- a direct model to predict the effect of the control action on the system,
- a controller based on the inverse of the process model.

In this case, the direct and inverse models are neuro-fuzzy models.

III. Neuro-Fuzzy Model

Takagi-Sugeno (T-S) type of fuzzy model is often used for modeling of a majority of highly nonlinear systems. Direct and inverse models can be expressed by T-S type model with n rules. The i-th rule of the T-S model for m-inputs (in) is described as follows

$$R_i : \text{if } in_1 \text{ is } A_{1i} \text{ and} \ldots in_m \text{ is } A_{mi}, \quad \text{then} \quad out_i = p_{0i} \tag{7}$$

where out_i is the output of the i-th rule (i=1,2,…, n), A_{1i} and A_{mi} are the fuzzy sets, and p_{0i} is the parameters vector.

The output is expressed as weighted average of the individual rules' consequents

$$out = \frac{\sum_{i=1}^{n} \mu_i \, out_i}{\sum_{i=1}^{n} \mu_i} \tag{8}$$

where the weights μ_i are

$$\mu_i = \prod_{j=1}^{n} A_{ji}(in_j) \tag{9}$$

$\prod$ is fuzzy operator, generally been applied as the min or the product operator and n is number of rules.

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 has two inputs $y(k\text{-}1)$, $u(k)$ and output is $y(k)$ and the inverse model has three inputs $u(k\text{-}1)$, $w(k+1)$, $y(k\text{-}1)$ and output is $u(k)$ as is depicted in Fig. 2.

The direct model of the controlled process is Takagi-Sugeno (T-S) fuzzy model, membership functions are built on the triangular distribution curve. The fuzzy model has been designed based on input-output measurement data. Still, compared to other nonlinear techniques, fuzzy models provide more transparent representation of the identified model.

Parameters of the fuzzy model are adapted by means of a 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, the process outputs are swapped with inputs and the same neuro-fuzzy algorithm is used to create 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 designed by using of fuzzy clustering algorithm.

IV. Case Study and Simulation Results

A. Thermo-Optical Plant

Thermo-optical plant is a simple laboratory physical model of thermo-dynamical and optical systems called DIGICON USB thermo-optical plant (Fig. 3). Its thermal channel contains one heater represented by an electric bulb and one cooler represented by a small fan [6]. The output of this channel is represented by temperature inside the tube. Measurement of the output value is represented by a thermal sensor. The second dynamics is formed by the optical channel. Within this channel it is possible to generate light by LED and measure the intensity of this light by photo resistor. The optical channel is even more comfortable for conducting experiments, because the time constants are much smaller compared to the thermal channel. The base of the model covers also electronic part. This part includes one connector for input (voltage) and two other connectors for data communication. One of these connectors is used for communication with the data acquisition card AD512 and another one is the USB port that can be connected directly to the computer (instead of using an expensive data acquisition card). The front panel of the base includes five information LEDs. The body of the electronic part is equipped with integrated circuits for communication and signal conversion [7].

From the input-output characteristic depicted in Fig. 4, the working points WP_1=(3.21, 20.8) and WP_2=(3.75, 24.2) have been chosen. The following experiment has been performed – step (in time 30 sec.) from WP_1 to WP_2. The step response has been recorded. Then times $t_{0.33}$ and $t_{0.7}$ as well as $h_s(\infty)$ according to Fig. 5 have been measured. Transfer function (11) has been calculated.

Fig. 3. Thermo-optical plant

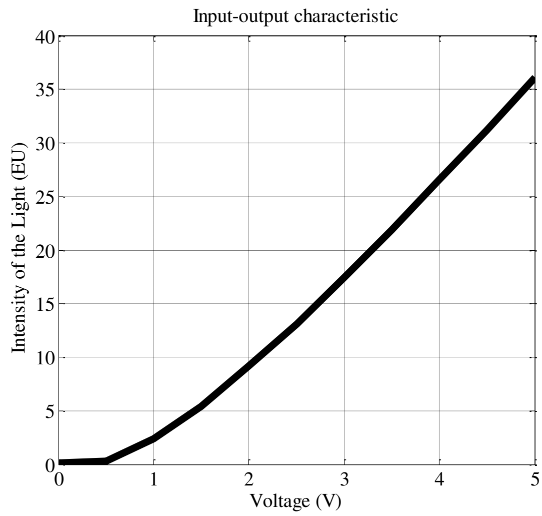

Fig. 4. Input-Output characteristic of the thermo-optical plant.

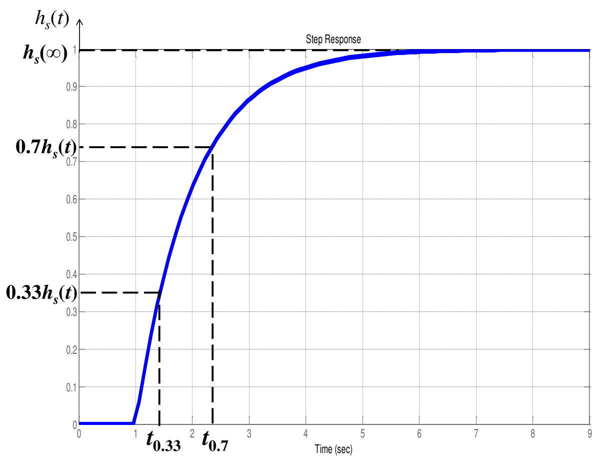

Fig. 5. Aperiodic step response.

The coefficient of transfer function K is given by (10) - if the input step isn't unit step, K is calculated from Δy and Δu, where Δy and Δu are the values of steady state output variable and input variable [15], respectively

$$K = h_s(\infty)\,,\ K = \frac{\Delta y}{\Delta u} \tag{10}$$

Transfer function is calculated from the process step response ($t_{0.33}$=0.24 sec and $t_{0.7}$=0.32 sec):

$$\left.\begin{aligned} T &= 1.245(t_{0.7} - t_{0.33}) \\ T_d &= 1.498 t_{0.33} - 0.498 t_{0.7} \end{aligned}\right\} \Rightarrow G(s) = \frac{K}{Ts+1} e^{-T_d s} \tag{11}$$

For the IMC structure shown in Fig. 2, $\hat{G}(s)$ is expressed as

$$\hat{G}(s) = \frac{9.17}{0.1s+1} e^{-0.2s} \tag{12}$$

The measured plant step response and its approximation (12) are shown in Fig. 6.

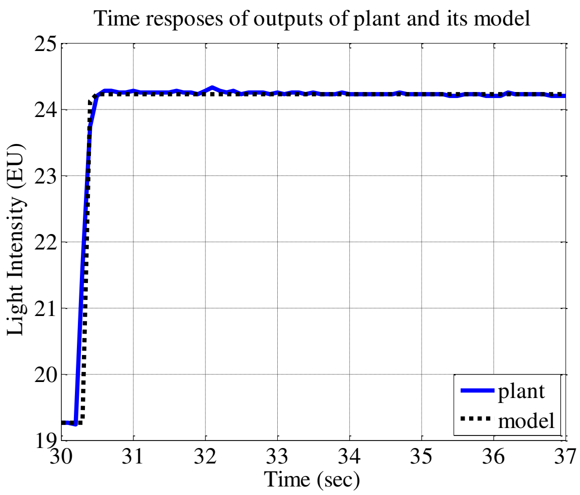

Fig. 6. The measured plant step response and its approximation (9).

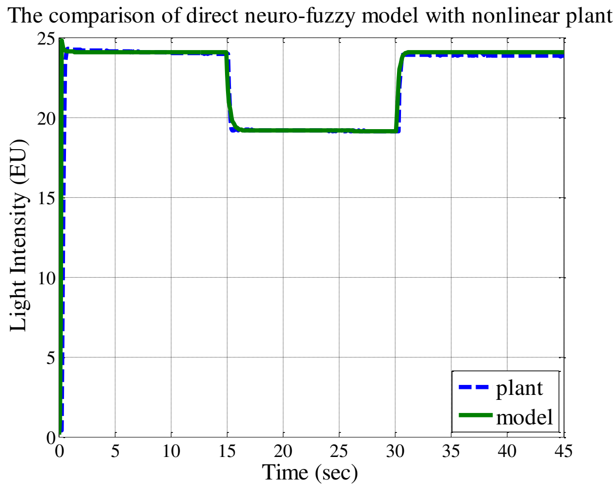

Fig. 7. The comparison of time responses of outputs from direct neuro-fuzzy model and nonlinear plant.

Direct and inverse neuro-fuzzy models have been designed for the Neuro-Fuzzy IMC structure shown in Fig. 2. Direct T-S fuzzy model has been designed based on step change between operating points WP_1 and WP_2. The direct model has five triangular membership functions for both inputs $y(k\text{-}1)$, $u(k)$ and output $y(k)$ membership functions are constant. Then an inverse neuro-fuzzy model making use of subtractive clustering method was designed with parameters: range of influence is 0.5, squash factor is 1.25, accept ratio is 0.5 and reject ratio is 0.15. The inverse model has three inputs $u(k\text{-}1)$, $w(k\text{+}1)$, $y(k\text{-}1)$ and output is $u(k)$. Rules of both neuro-fuzzy models were generated automatically in anfiseditor [16]. The direct model has 25 rules and the inverse model has 2 rules.

Time responses of output from direct neuro-fuzzy model and nonlinear plant is shown in Fig. 7.

B. *Control of Plant*

In implementation of IMC scheme (Fig. 1), the process model (9) may be separated into invertible $\hat{G}^-$ and noninvertible part $\hat{G}^+$ (unstable poles, time delays, etc.) with the steady state gain $\hat{G}(s)= \hat{G}^+\hat{G}^-$

$$\hat{G}^+ = e^{-0.2s} \approx 1 - 0.2s, \quad \hat{G}^- = \frac{9.17}{0.1s+1} \tag{13}$$

The IMC controller is computed based on (5) with $G_{Y/W}(s)$ from (6), where λ=0.3 and n=1. Time constant of the closed-loop system λ has been chosen on base of knowing the time constant of the system being controlled (12). Transfer function of IMC controller is

$$G_{RIMC}(s) = \frac{0.1s+1}{2.75s+9.17} \tag{14}$$

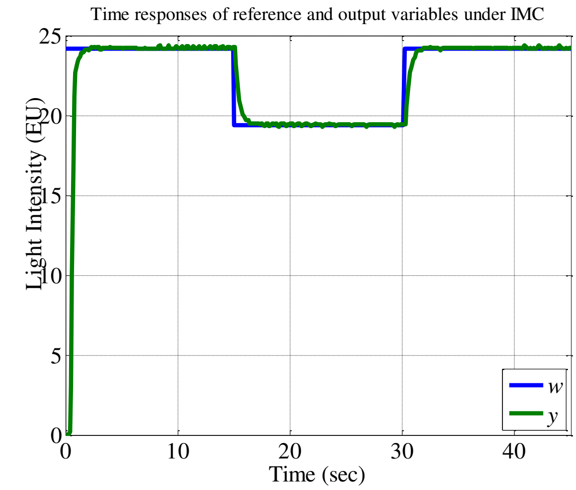

Fig. 8. Time responses of the controlled and reference variables of the process under IMC.

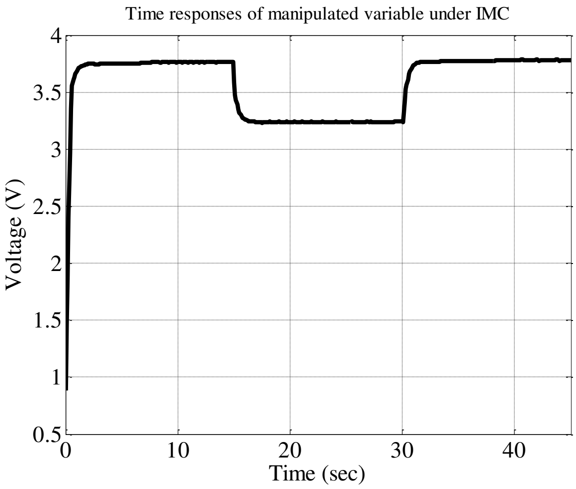

Fig. 9. Time response of the manipulated variable under IMC.

Time responses of the controlled and reference variables under IMC as depicted on Fig. 1 are shown on Fig. 8. Time responses of manipulated variable are shown on Fig. 9.

Time responses of both the controlled and reference variables under NFIMC structure from Fig. 2 are shown on Fig. 10. Time responses of manipulated variable under NFIMC are shown on Fig. 11.

The stability and convergence of the proposed methods is guaranteed via Lyapunov synthesis [1].

Control performance of NFIMC was compared with conventional PID controller. Method of direct synthesis [17] has been chosen for controller tuning. Parameters of PI controller are P=0.02 and I=0.2. Comparison of NFIMC with PI controller is shown on Fig. 12.

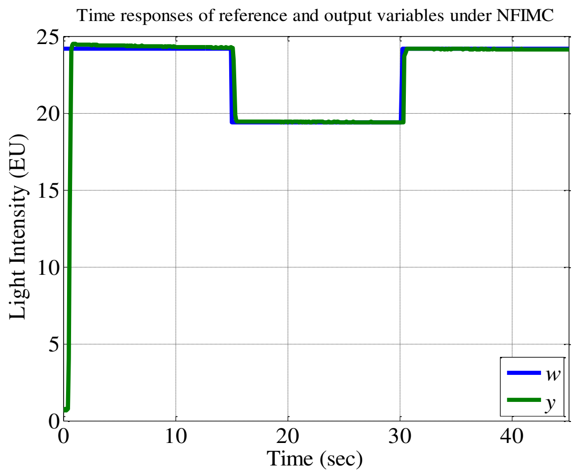

Fig. 10. Time responses of the controlled and reference variables of the process under NFIMC.

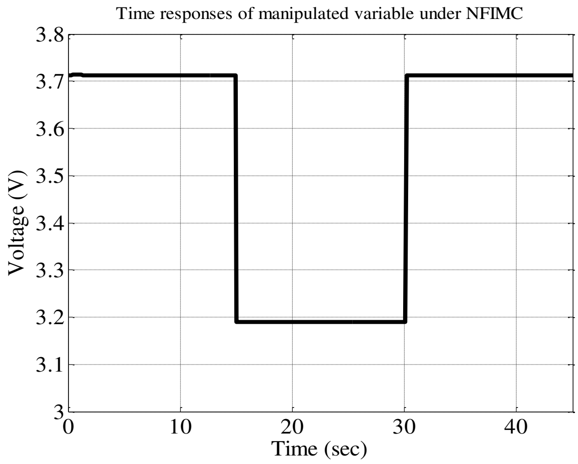

Fig. 11. Time responses of the manipulated variable of the process under NFIMC.

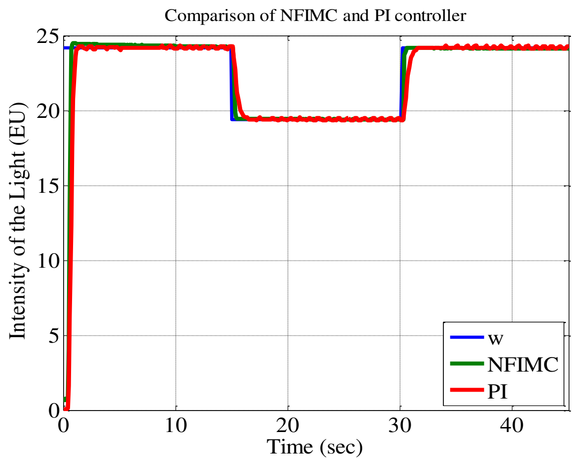

Fig. 12. Time responses of the controlled and reference variables under NFIMC and PI control.

V. CONCLUSIONS

In this paper IMC and NFIMC for control of nonlinear process are designed. The proposed IMC structure is simple and convenient to design.

The control performance of such a controller depends on accuracy of the process model.

The NFIMC method consists of a direct model and an inverse neuro-fuzzy model of the laboratory process using an adaptive neuro-fuzzy inference system. These models are used directly in the IMC structure. FNIMC is very effective method, which is based on neuro-fuzzy model and existence of inverse neuro-fuzzy model. The performance of FNIMC depends on the accuracy of neuro-fuzzy model. These proposed control algorithms are applied to control of thermo-optical plant to show the effectiveness of the proposed algorithms.

Our future aim of research will be design of control algorithm with considering input and output constraints.

ACKNOWLEDGMENT

This paper has been supported by the Slovak Scientific Grant Agency, Grant No. 1/0475/16.

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