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An Modified Approximate Internal Model-based Neural Control

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Abstract— **An modification of the Approximate Internal Model-based Neural Control (AIMNC), using Multi Layer Perceptron (MLP) neural networks is proposed. A necessary condition that the system provides zero steady-state error for a constant reference and constant disturbances is derived. In the proposed control strategy only one neural network, which is the neural model of the plant, needs to be trained off-line. An inverse neural controller can be directly obtained from the neural model without need for a further training. Simulations demonstrate performance improvement of the proposed AIMNC modification.**

Keywords-input-output approximation; neural networks; nonlinear internal model control; zero steady-state error;

I. INTRODUCTION

Different control techniques based on internal model are often used for the control of nonlinear processes [1]-[5]. It is known that Internal Model Control (IMC) compared to other closed loop control techniques have advantages in terms of robustness against disturbances and a model mismatch [3]. If the process and the controller are input-output stable, and if the internal model is perfect, then the control system is stable.

The IMC is based on the process model and its inversion embedded in the controller. Even when the process model and the controller are nonlinear, positive characteristics of the IMC strategy in terms of stability, robustness and accuracy of the steady-state provides a good basis for its application in the control of nonlinear processes exposed to unknown disturbances [1]. Since Neural Networks (NNs) are universal approximators, their usage is a convenient way to model the nonlinear input–output mapping and can be used within the IMC structure shown in Fig. 1, as the internal process model as well as inverse controller [6]-[8]. Although different procedures of determining the appropriate neural model of the plant and controller were used in past, it has been observed that the performance of neural IMC became better when a connection between these procedures was established [9], [10].

The aim of this paper is to demonstrate the possibilities of neural IMC based on internal model approximation [11]-[13], which provides zero steady-state error in the case of the constant reference and constant disturbances. The necessary condition that the system provides zero steady-state error regardless of the model order and its accuracy is derived. In this paper, neuro model identification, calculation of the control law and comparison of the modified AIMNC strategy with performance of the fixed and adaptive IMC is presented.

II. AIMNC CONTROLLER DESIGN

A. The plant modeling

A general input–output representation for an n-dimensional nonlinear discrete time system with relative degree d is [14]

$$y(k+d) = f[w_k, u(k)], \tag{1}$$

where $w_k = [y(k), y(k-1),..., y(k-n+1), u(k-1),..., u(k-n+1)]$, $u(k) \in R$, and $y(k) \in R$ are the input and output of the system, respectively, $f : R^n \times R^n \to R$ and $f \in C^\infty$. Equation (1) represents *Nonlinear Autoregressive Moving Average* (NARMA) model. Different types of NNs have been considered for modeling and control of nonlinear dynamical systems. In this paper, a Multi Layer Perceptron (MLP) NN has been used for modeling of nonlinear discrete time dynamical systems due to its general approximation abilities. If there is appropriate number of neurons in the hidden layers and adequately determined free parameters, MLP NN can approximate arbitrary continuous nonlinear function on a compact subset C^∞ of $R^n \times R^n$ to the desired accuracy [6].

NN NARMA model is as follows [11],[12]:

$$y(k+d) = N[w_k, u(k)] + \xi_k, \tag{2}$$

where $N[\bullet]$ is a neuro model of the nonlinear dynamical system and the weight vector of the NN is omitted for simplicity, ξ_k is an model error. Taking into account the disturbances acting on the plant, (2) can be written as

$$y(k+d) = N[w_k, u(k)] + v_k, \tag{3}$$

where v_k takes into account the effect of uncertainties (model error ξ_k and disturbances).

B. An approximation of NN model

NN controller in the IMC control structure is an inversion of the NN model of the plant [6]. Hence, it is necessary to find the inversion of nonlinear mapping, represented by the NN, that models the nonlinear plant [1],[2]. Since the output of the NN model (3) is nonlinearly dependent on its input, it is difficult to derive its inversion and related control law. Thus in [11]-[13], an approximate model is firstly derived for the system (3) using Taylor expansion of $N[w_k, u(k)]$ with respect to $u(k)$ around $u(k-1)$ as

$$\begin{aligned} y(k+d) &= N[w_k, u(k)] + v_k = \\ &= N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u(k) + R_k + v_k, \end{aligned} \tag{4}$$

where $N_1[w_k, u(k-1)] = (\partial N[w_k, u(k-1)])/(\partial u(k))$ and $\Delta u(k) = u(k) - u(k-1)$. Remainder R_k is as follows

$$R_k = N_2[w_k, \zeta_k](\Delta u(k))^2 / 2, \tag{5}$$

where $N_2[w_k, \zeta_k] = \left(\partial^2 N[w_k, \zeta_k)]\right)/\left(\partial u^2(k)\right)$ with ζ_k as a point between $u(k)$ and $u(k-1)$.

Based on the assumptions made in [11], after neglecting the reminder R_k and the uncertainty v_k in (4), the NN approximate model $\hat{y}_m(k+d)$ in the input–output form is derived as follows

$$\hat{y}_m(k+d) = N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u(k). \tag{6}$$

In (6), the control increment $\Delta u(k)$ appears linearly in the output of the NN approximate model $\hat{y}_m(k+d)$, thus the design of the inverse NN controller can be simplified greatly. To calculate the NN approximate model (6) and NN controller, the calculation of $N_1[w_k, u(k-1)]$ is needed. In this paper the basic MLP structure with two hidden layers, shown in Fig. 2, has been used for modeling of non-linear discrete time dynamical systems. Inputs of the NN plant model at the time instant *k* are w_k and $u(k-1)$. MLP in the first and second hidden layer has neurons with hyperbolic tangent activation function and bias input.

A linear activation function and bias input are used for the output neuron. Double-layered MLP can be expressed as

$$N[w_k, u(k)] = W_{32}\sigma[W_{21}\sigma[W_{11}w_k + W_{12}u(k) + b_1] + b_2] + b_3, \tag{7}$$

where $W_{10} = [W_{11} \quad W_{12}]$, $W_{10} \in R^{L_1 x 2n}$, $W_{12} \in R^{L_1 x 1}$, $W_{21} \in R^{L_2 x L_1}$ and $W_{32} \in R^{1 x L_2}$ are matrices of weights within the first hidden layer, second hidden layer, and the output layer of the NN, b_1, b_2 and b_3 are bias vectors, and $\sigma(X) = \left(e^X - e^{-X}\right)/\left(e^X + e^{-X}\right)$ is the vector of hyperbolic tangent activation functions with input vector X.

If double-layered MLP $N[w_k, u(k)]$ is given by (7), then following the idea in [12], $N_1[w_k, u(k-1)]$ is given by (8). Since the derivative of $\sigma(X)$ is $\sigma' = I_{Li} - \sigma^2$ with I_{Li} as a L_i-dimensional unit matrix and L_i as the number of neurons in *i*-th hidden layer, one has

$$N_1[w_k, u(k-1)] = W_{32}(I_{L_2} - \sigma_2\sigma_2^{\,T})W_{21}(I_{L_1} - \sigma_1\sigma_1^{\,T})W_{12}, \tag{8}$$

with $\sigma_1 = \sigma[W_{11}w_k + W_{12}u(k-1) + b_1]$ and $\sigma_2 = \sigma[W_{21}\sigma_1 + b_2]$.

To determine the plant model and the controller only one neural network, whose parameters are trained off-line, is required. After that, the parameters of the obtained neural network are used to calculate the approximate neural model and its inversion as the controller in the IMC structure.

C. A controller design

From (6) the control increment $\Delta u(k)$ is as follows

$$\Delta u(k) = (\hat{y}_m(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)]. \tag{9}$$

The control increment in (6) can be divided into two parts [12]

$$\Delta u(k) = \Delta u_n(k) + \Delta u_c(k), \tag{10}$$

where $\Delta u_n(k)$ is the nominal control increment and $\Delta u_c(k)$ is used to compensate the model error and disturbances. Using (10), (6) becomes

$$\hat{y}_m(k+d) = N[w_k, u(k-1)] + N_1[w_k, u(k-1)](\Delta u_n(k) + \Delta u_c(k)). \tag{11}$$

When the model is exact and there are no disturbances, i.e. in the nominal case, the NN approximate model is as follows

$$\hat{y}_m(k+d) = N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u_n(k). \tag{12}$$

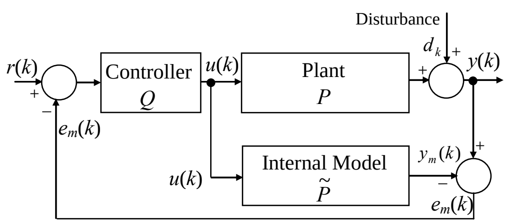

Figure 1. The IMC structure

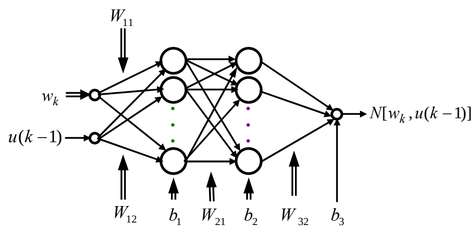

Figure 2. Double-layered MLP structure

If the NN approximate model given by (12) has a stable inverse, then the nominal control increment $\Delta u_n(k)$ can be calculated directly as follows

$$\Delta u_n(k) = (r(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)], \quad (13)$$

where $r(k+d)$ is the reference signal at time instant $(k+d)$. The nominal control law is determined as follows

$$u(k) = u(k-1) + \Delta u_n(k). \quad (14)$$

If the NN approximate model given by (12) has an unstable inversion, it is needed that (13) should be modified by introducing the parameter α, as proposed in [12], according to

$$\Delta u_n(k) = \alpha(r(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)], \quad (15)$$

where $0 < \alpha \le 1$. Introduction of the parameter α ensure that the control law given by (14) is bounded. The parameter α can be 1 in the case of NN approximate model has the stable inverse. Conditions for the stability of the nominal NN controller (14) are detailed in [12].

In the presence of the plant model error and disturbances, substituting (10) in to (4), gives

$$\begin{aligned} y(k+d) &= N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u_n(k) \\ &+ N_1[w_k, u(k-1)]\Delta u_c(k) + R_k + v_k. \end{aligned} \quad (16)$$

Define NN approximate model error $\varepsilon(k)$ as

$$\varepsilon(k) = y(k) - \hat{y}_m(k). \quad (17)$$

The control increment $\Delta u_c(k)$ for compensation of the model error and disturbances is as follows [12]

$$\Delta u_c(k) = -\varepsilon(k) / N_1[w_k, u(k-1)]. \quad (18)$$

Based on (10), (15) and (18) the control law is expressed as

$$\begin{aligned} u(k) &= u(k-1) + \alpha(r(k+d) - N[w_k, u(k-1)]) \\ &/ N_1[w_k, u(k-1)] - \varepsilon(k) / N_1[w_k, u(k-1)]. \end{aligned} \quad (19)$$

The control law (19) consists of the nominal NN controller and uncertainties compensation. The analysis of robustness and stability of the control law (19) is given in [12].

The conceptual structure of the modified AIMNC with the control law given by (19) and NN approximate model given by (12) is shown in Fig. 3. With $S(z^{-1})$ is labeled set point filter, with $F(z^{-1})$ robustness filter, where z^{-1} is backward shift operator [15]. The role of the blocks marked with "Scale" in Fig. 3. will be explained in paragraph IV.

III. AIMNC WITH ZERO STEADY-STATE ERROR

A positive feature of the IMC control structure that zero steady-state error in the system can be achieved if we ensure that the steady-state gain of the controller is inverse value of the steady-state gain of the model [3]. The performances of the AIMNC structure are given in [12], without the necessary conditions that the system has zero steady-state error for the case of a constant reference and constant disturbances. From Fig. 3. it is evident that the AIMNC structure differs from the classical IMC structure given in Fig. 1. A signal, which is input to the NN approximate plant model is different from the control signal to the plant, and it is necessary to define the conditions under which we can achieve zero steady state error.

Consider the conditions under which it is possible to achieve the satisfactory accuracy of the steady-state with AIMNC structure in Fig. 3. in the case of the constant reference signal and constant disturbances. If the system has zero steady-state error then $y(k) = r(k)$ and $\Delta u(k) = u(k) - u(k-1) = 0$, then using (17) and (19), one has

$$\begin{aligned} &\Delta u(k) = \alpha(r(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)] \\ &- \varepsilon(k) / N_1[w_k, u(k-1)] = 0, \\ &\quad \alpha r(k+d) - \alpha N[w_k, u(k-1)] - \varepsilon(k) = 0, \\ &\alpha r(k+d) - \alpha N[w_k, u(k-1)] - y(k) + \hat{y}_m(k) = 0. \end{aligned} \quad (20)$$

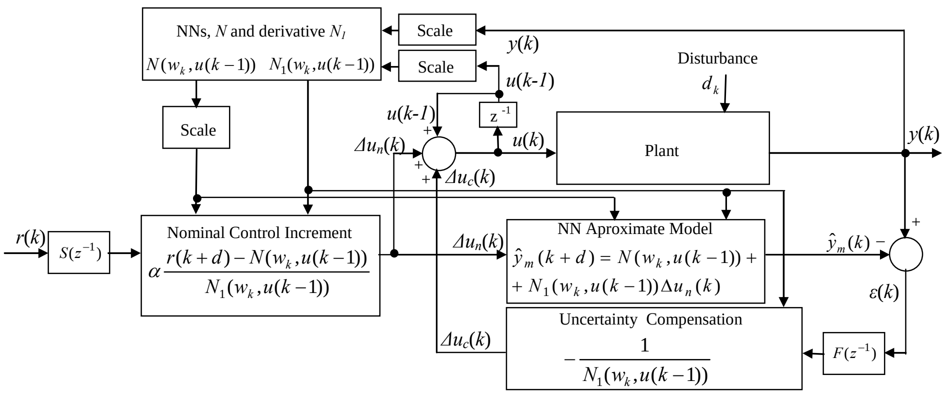

Figure 3. The conceptual structure of the modified AIMNC

In the steady-state $\hat{y}_m(k) = \hat{y}_m(k+1)) = ... = \hat{y}_m(k+d)$. Substituting (12) and (15) in to (20), one has

$$\begin{aligned} &\alpha r(k+d) - \alpha N[w_k, u(k-1)] - y(k) + N[w_k, u(k-1)] \\ &+ \alpha(r(k+d) - N[w_k, u(k-1)]) = 0, \\ &2\alpha(r(k+d) - N[w_k, u(k-1)]) = y(k) - N[w_k, u(k-1)], \\ &\alpha = \frac{1}{2} \cdot \frac{y(k) - N[w_k, u(k-1)]}{r(k+d) - N[w_k, u(k-1)]}. \end{aligned} \tag{21}$$

In the steady-state one has $r(k) = r(k+1) = ... = r(k+d)$ and the system will have zero steady-state error if $y(k) = r(k) = r(k+1) = ... = r(k+d)$. It follows from (21) that $\alpha = 0.5$ is the necessary condition that the system in Fig. 3. has zero steady-state error in the case of the constant reference signal and constant disturbances.

IV. Performance of the AIMNC Strategy

We conducted a sequence of simulations to show the performance of the AIMNC strategy and verify that for the value $\alpha = 0.5$ system achieves zero steady-state error for the constant reference signal and constant disturbances. The selected plant is described by nonlinear difference equation

$$y(k+1) = 0.5\sin(y(k)) + 3u(k) + \frac{\sin(y(k)u(k))}{1+y^2(k)} + d_k, \tag{22}$$

where d_k is the disturbance.

A. The NN model of the plant

The basic MLP structure with two hidden layers, described in Fig. 2, has been used for modeling of the nonlinear discrete dynamical system. Inputs of the NN for modeling at time instant k are $w_k = [y(k)]$ and $u(k-1)$, and output is $y(k+1)$. MLP in each hidden layer has 10 neurons with hyperbolic tangent activation functions and bias inputs. The linear activation function with a bias term are used for the output neuron.

Training set consists of 500 pairs $y(k)$ and $u(k-1)$, which represented the input vector of the MLP at time instant *k*, and desired output values $y(k+1)$ were obtained from (22). The values of $u(k), k = 1,...,500$ were chosen as random numbers in the range of $[-2 \quad 2]$, and generated 501 values of $y(k)$ were in the range $[-6.45 \quad 6.55]$.

For the NN training, a MATLAB function "newnarxsp" has been used. The inputs to the MLP and outputs were scaled to the range $[-1 \quad 1]$, training algorithm used *Levenberg-Marquart* method, a number of training epochs was 1000 and achieved a mean square error of 5.74x10^{-6}. As a result of off-line training we obtained matrices $W_{10} = [W_{11} \quad W_{12}]$, $W_{10} \in R^{10\times 2}$, $W_{12} \in R^{10\times 1}$, $W_{21} \in R^{10\times 10}$ and $W_{32} \in R^{1\times 10}$ and vectors b_1, b_2 and b_3, with dimensions 10x1, 10x1 and 1x1, respectively.

B. The accuracy of AIMNC in steady-state

We performed a simulation of the AIMNC strategy given in Fig. 3. with the obtained MLP. Set point filter and robustness filter were set as $S(z^{-1}) = 1$ and $F(z^{-1}) = 1$, respectively. The blocks marked with a "Scale" in Fig. 3. are introduced for the reason that the off-line training of MLP performs scaling of inputs and the output to the desired range $[-1 \quad 1]$. So to calculate $N[w_k, u(k)]$ in the AIMNC structure it is necessary to scale inputs within the range $[-1 \quad 1]$, and the output in the range $[-6.45 \quad 6.55]$.

The parameter α value of 0.5 was chosen based on the necessary condition to achieving the zero steady-state error in case of the constant reference signal and constant disturbances acting on system shown in the Fig.3. Reference $r(k)$ has been chosen to take the values of 0.5, 6, 0.5, -6 and 0, successively for five period of 100 samples, and disturbance d_k had a non-zero value from samples 230 to 260, i.e. the value equal 1 when the reference $r(k)$ had the value of 0.5.

Fig. 4. shows satisfactory behavior of the proposed modified AIMNC strategy and confirms that the choice of parameter $\alpha = 0.5$ achieves zero steady-state error for the constant reference signal and constant disturbances. Additional testing of the accuracy was done through simulation for different values of the parameter $\alpha = 0.51$ and $\alpha = 0.49$. Fig. 5. shows the part of system response from samples 230 to 260, for the reference signal $r(k) = 0.5$ and disturbance $d_k = 1$. Clearly, the system has zero steady-state error for the constant reference signal and constant disturbance only in the case when $\alpha = 0.5$.

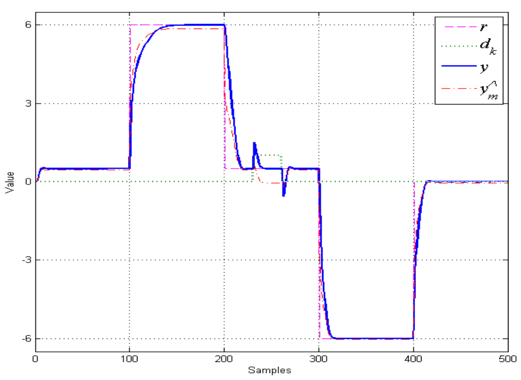

Figure 4. Reference r , disturbance d_k , system y and model $\hat{y}_m$ outputs

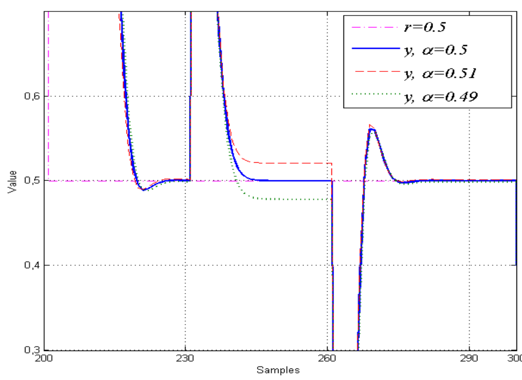

Figure 5. System output y for different values of α

C. *The robustness to the model mismatch*

In addition to the stability and accuracy of the control systems one of the important feature is robustness to the model mismatch that is used for the controller design, and as an integral part of the AIMNC structure. The simulation of the AIMNC strategy for the plant described by equation

$$y(k+1)=0.7\sin(y(k))+2.5u(k)+\frac{\sin(0.7y(k)u(k))}{1.2+y^2(k)}+d_k, \qquad (23)$$

with already trained NN approximate models have been performed. The plant model given by (23) is significantly different from the nominal plant given by (22) in order to test the robustness of the modified AIMNC strategy.

Fig. 6. show satisfactory behavior of the proposed modified AIMNC strategy for the significant model mismatch. Also, when the significant model mismatch exist the system has zero steady-state error for the constant reference signal and constant disturbances only in the case with the value $\alpha = 0.5$.

D. *The performance verification*

The comparison of the AIMNC strategy with respect to performance of the fixed and adaptive IMC is presented. Design of the fixed and adaptive IMC are presented in [16].

1) Fixed linear IMC: Simulation of the IMC control strategy in Fig. 1. with fixed parameters of the linear internal model and the controller was performed. An adjustment of the controller parameters is achieved on the basis of the obtained linear model of the plant. The obtained linear internal model describes well the dynamics of the selected plant given by (22) for changes of the plant output in the range of 0 to 3. Internal model $\tilde{P}(z^{-1})$ is given by (24), and controller $Q(z^{-1})$ described by (25) was determined by pole-zero placement of the discrete transfer function [17]- [19].

$$\tilde{P}(z^{-1})=\frac{b_1 z^{-1}}{1-a_1 z^{-1}}=\frac{2.8492z^{-1}}{1-0.08z^{-1}}, \qquad (24)$$

$$Q(z^{-1})=\frac{(1-p_1)}{b_1}\cdot\frac{(1-a_1 z^{-1})}{(1-p_1 z^{-1})}=\frac{(1-0.8)}{2.8492}\cdot\frac{(1-0.08z^{-1})}{(1-0.8z^{-1})}. \qquad (25)$$

The transfer function of the controller is in given form that provides the closed-loop system has zero steady-state error. Selecting the desired pole of the closed-loop system determines the quality of the step response.

2) Adaptive IMC: Simulation of the adaptive control based on internal model was performed. In the case of adaptive IMC strategy, the method of on-line calculation of the controller parameters based on parameter estimation of the plant dynamic model is applied [16]. Adaptation of the parameters a_1 and b_1 of the model given by (24) and the controller given by (25), respectively, is performed using the recursive least-squares mean algorithm with forgetting factor [15]. For adaptive dynamic model of the plant y_{AIMCm} was chosen in the form:

$$y_{AIMCm}=a_1 y_{AIMCm}(k-1)+b_1 u(k-1). \qquad (26)$$

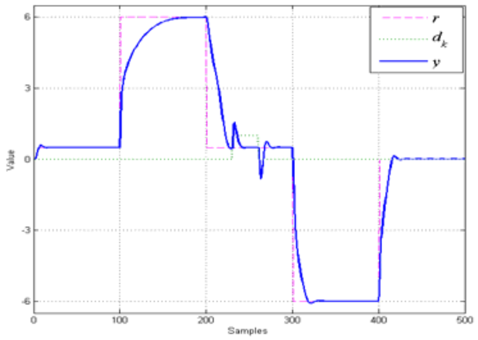

Figure 6. System output y for the plant given by (23)

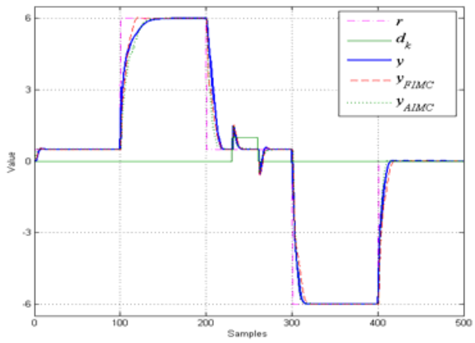

Figure 7. Reference r, disturbance d_k and outputs y, y_{FIMC} and y_{AIMC}

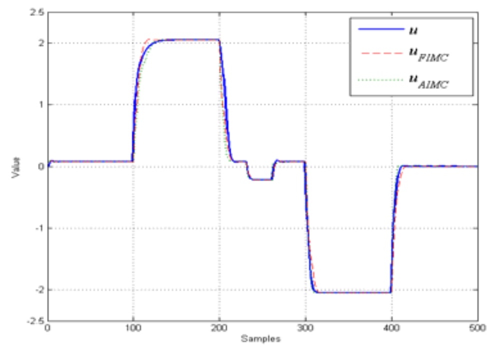

Figure 8. *Control actions* u, u_{FIMC} *and* u_{AIMC}

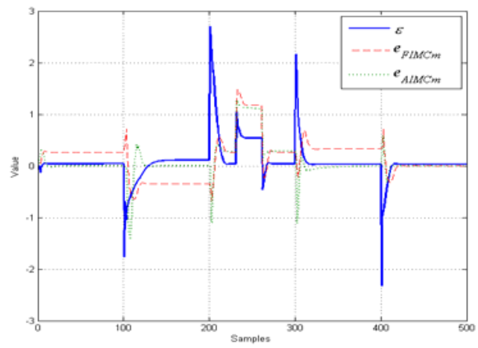

Figure 9. Model errors ε, e_{FIMCm} and e_{AIMCm}

TABLE I. MEAN SQUARE ERROR

	AIMNC	Fixed IMC	Adaptive IMC
MSE	0.7004	0.8210	0.7246

Using this parallel model, the value of the controller output, in the steady state, is the exact inverse of the plant model output, which is a necessary condition for the closed loop system has the zero steady-state error. Recursive equations for the covariance matrix $P(k)$ and the vector of the parameters $\Theta = [a_1 \quad b_1]^T$ calculations are shown below

$$P(k) = \frac{1}{\lambda}\left[P(k-1) - \frac{P(k-1)\varphi(k)\varphi^T(k)P(k-1)}{\lambda - \varphi^T(k)P(k-1)\varphi(k)}\right], \tag{27}$$

$$\Theta = \Theta + P(k)\varphi(k)e_{AIMCm}(k), \tag{28}$$

where $\lambda = 0.99$ is a forgetting factor, $\varphi(k) = [y_{AIMCm}(k) \quad u(k-1)]^T$ is regression vector and $e_{AIMCm}(k) = y(k) - \varphi^T(k)\Theta$ is the model error. The initial values of the covariance matrix and vector of the parameters were, respectively, $P(0) = 5 \cdot I_{[2\times 2]}$, and $\Theta = [0.08 \quad 2]^T$.

The desired pole of the closed-loop system has been calculated as $p_1 = 0.95 - (1 - a_1)/2$. The set point filter with transfer function $S(z) = (1-0.51)/(1-0.51z^{-1})$ was used.

3) Performance comparison: Comparative analysis of important signals of the considered control strategies confirmed the satisfactory performance of the modified AIMNC control law.

Fig. 7. shows the reference and the system outputs with modified AIMNC, fixed and adaptive IMC control law. All control strategies have satisfactory behavior in the nominal case and under disturbance and zero steady-state error. All considered IMC control strategies have similar control signals, as was expected, since all control strategies have satisfactory performance, Fig.8. Model errors of the considered control strategies are shown in Fig. 9. Although internal model for adaptive IMC has the smallest error in the steady state when there is no disturbance, modified AIMNC achieves better performance. For the performance of the IMC strategy it is important to note that the controller represents the inversion of the internal model as accurate as possible.

Values of the Mean Square Error (MSE) for 500 sampling periods are given in the Table 1. MSE for modified AIMNC strategy is the smallest.

V. CONCLUSION

This paper has presented an improvement of the AIMNC structure. The procedure of designing the model and controller is shown and derived the necessary condition for the accuracy of the system in steady state for the constant reference and constant disturbances. The necessary condition for the accuracy of AIMNC strategy derived in this paper is the significant contribution to the procedure of designing the system based on the NN approximate internal model, since it is one of the most common requests that the automatic control system provides the zero steady-state error.

A series of simulations has confirmed the accuracy of the modified AIMNC structure at steady state. Detailed comparison of the AIMNC strategy with performance of the fixed and adaptive IMC is carried out and demonstrate satisfactory behavior of modified AIMNC strategy.

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