A Modified Approximate Internal Model-based Neural Control for the Typical Industrial Processes

Jasmin Igic and Milorad Bozic

***Abstract*—A modification of the Approximate Internal Model-based Neural Control (AIMNC), using Multi Layer Neural Network (MLNN) is introduced. A necessary condition that the system provides zero steady-state error in case of the constant reference and constant disturbances is derived. In the considered control strategy only one neural network (NN), which is the neural model of the plant, should 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 modified AIMNC strategy. An extension of the modified AIMNC controller for the typical industrial processes is proposed.**

***Index Terms*—Industrial processes, Neural networks, Nonlinear internal model control, Zero steady-state error.**

Original Research Paper
DOI: 10.7251/ELS1418046I

I. Introduction

We may imagine an Internal Model Control (IMC) architecture as a system with two degrees of freedom consisting of plant model dynamics and some approximation of the inverse dynamics of the plant model. In this respect the process as well as its approximate inverse dynamics must be stable. If the dynamics of the process is not stable, then the objective of the system design using an IMC approach is, primarily, stabilization of the process. Such a stabilized system is then viewed as an equivalent process that must satisfy forward-mentioned characteristics in terms of stability.

In addition to stability not less important aspect is the system accuracy. An architecture of the IMC has many positive characteristics in terms of stability, robustness and accuracy in a steady-state with respect to one degree of freedom approaches developed in the area of control engineering [1],[2].

The IMC design algorithms based on linear models have attracted much attention of control theorists, as well as of practitioners, especially within industrial applications in 1980s. Almost in parallel with such developments many successful trials were conducted using the IMC architecture combined with some kind of adaptation mechanism applied to control slowly varying processes [3],[4].

Further more, as the MLNN have been proved as universal approximators they were used in IMC architectures to control nonlinear processes [2],[5]-[10]. In that sense an Approximate Internal Model-based Neural Control (AIMNC) and its modification were proposed for unknown nonlinear discrete time processes [11]-[13]. High performance of the mentioned algorithms have been demonstrated at applications to some benchmark examples of industrial processes. However, we have noticed unacceptable behavior in applications of such designs to control slow industrial processes. The typical industrial processes show some accumulation effects plus dead time, i.e. they usually have a very slow dynamics.

The well-known examples of such processes are tanks, where the liquid level is controlled by using the difference between the input and output flow rates to form a manipulated variable [14], so in this paper we consider a double tank system as a plant.

To overcome the above mentioned problem in applications of the modified AIMNC algorithm, in this paper we present an extension of the modified AIMNC controller design for slow nonlinear discrete time processes. This extension is based on a heuristic consideration of the needed control changes which provide requested tracking performance of the control system. However, simulation results confirm the validity of the proposed control design in cases of slow nonlinear discrete time processes.

The rest of the paper is organized as follows. In the Section II, a plant modeling, structure and the modified AIMNC controller design procedure are given. The Section III gives an extension of the modified AIMNC algorithm applied to double tank system together with simulation results demonstrating performance of the proposed approach in controlling slow processes. In the Section IV we give conclusions of the work.

Manuscript received 13 May 2014. Received in revised form 7 June 2014. Accepted for publication 11 June 2014.

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II. The AIMNC Controller Design

A. The plant modeling

A general input–output representation for an n-dimensional unknown nonlinear discrete time system with relative degree d is as follows [15]

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

where a vector w_k is composed of current $y(k)$ and past values of the output $y(k-1), i=1,\ldots,n-1$, and past values of the input $u(k-1), i=1,\ldots,n-1$, at the system, and nonlinear mapping is defined by $f: R^n \times R^n \to R$ with $f \in C^\infty$.

Modeling is the first step in designing a controller for unknown nonlinear system. Different types of neural networks have been considered for modeling and control of nonlinear dynamical systems. In this paper, a MLNN has been used for modeling of nonlinear discrete time dynamical systems due to its general approximation abilities. If there is an appropriate number of the neurons in the hidden layers and adequately determined free parameters, the MLNN can approximate arbitrary continuous nonlinear function on a compact subset C^∞ of $R^n \times R^n$ to the desired accuracy [16].

A Neural Network *Nonlinear Autoregressive Moving Average* (NARMA) model, i.e. NN NARMA model is defined as follows [11],[12]

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

where $N[\bullet]$ is a neural model of the nonlinear dynamical system and the weight vector of the NN is omitted for simplicity, ξ_k is an output 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 represents the effect of uncertainties (model error ξ_k and disturbances).

B. An approximation of the NN model

The NN controller in the IMC control structure represemts an inversion of the NN model of the plant [7]. Hence, it is necessary to find the inversion of nonlinear mapping, represented by the NN, that models the nonlinear plant [2], [3]. Thus [11]-[13], an approximate model for the system (3) using Taylor series expansion of $N[w_k, u(k)]$ with respect to $u(k)$ around $u(k-1)$ is 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 $N_1[w_k, u(k-1)] = \left(\partial N[w_k, u(k-1)]\right)/\left(\partial u(k)\right)$, $\Delta u(k) = u(k) - u(k-1)$, and remainder R_k is given by

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

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 output $\hat{y}_m(k+d)$ is derived as follows

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

Since in (6), a control increment $\Delta u(k)$ appears linearly in the output $\hat{y}_m(k+d)$ of the NN approximate model, thus the design of the inverse NN controller is facilitated. To obtain the NN approximate model (6) and NN controller, the calculation of $N_1[w_k, u(k-1)]$ is needed. As was shown in [12], when using the NN with two hidden layers and neurons with hyperbolic activation functions within it, both the NN model and a calculation of $N_1[w_k, u(k-1)]$ can be obtained by one neural network, whose parameters are trained off-line.

C. The controller design

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

$$\Delta u(k) = (\hat{y}_m(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)]. \tag{7}$$

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

$$\Delta u(k) = \Delta u_n(k) + \Delta u_c(k), \tag{8}$$

where $\Delta u_n(k)$ refers to the nominal control increment and $\Delta u_c(k)$ is used to compensate the model error and disturbances. Using (8), (6) becomes

$$\begin{aligned} &\hat{y}_m(k+d) = N[w_k, u(k-1)] \\ &+ N_1[w_k, u(k-1)](\Delta u_n(k) + \Delta u_c(k)). \end{aligned} \tag{9}$$

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

$$\hat{y}_m(k+d) = N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u_n(k). \tag{10}$$

If the NN approximate model given by (10) has a stable inverse, then the nominal control increment $\Delta u_n(k)$ can be obtained directly by

$$\begin{aligned} &\Delta u_n(k) = \\ &= (r(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)] \end{aligned}, \tag{11}$$

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

$$u(k) = u(k-1) + \Delta u_n(k). \tag{12}$$

If the NN approximate model given by (10) has an unstable inversion, it is necessary to modify (11) by introducing a parameter α, as proposed in [12], according to

$$\begin{aligned}&\Delta u_n(k) = \\ &= \alpha(r(k+d) - N[w_k, u(k-1)]) / N_1[w_k, u(k-1)],\end{aligned} \tag{13}$$

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

In the presence of the plant model error and disturbances, substituting (8) in to (4), gives

$$\begin{aligned}y(k+d) &= N[w_k, u(k-1)] + N_1[w_k, u(k-1)]\Delta u_n(k) \\ &+ N_1[w_k, u(k-1)]\Delta u_c(k) + R_k + v_k.\end{aligned} \tag{14}$$

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

$$\varepsilon(k) = y(k) - \hat{y}_m(k). \tag{15}$$

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

$$\Delta u_c(k) = -\varepsilon(k) / N_1[w_k, u(k-1)]. \tag{16}$$

Based on (8), (13) and (16) the control law is expressed as

$$\begin{aligned}&u(k) = u(k-1) + \alpha(r(k+d) \\ &- N[w_k, u(k-1)]) / N_1[w_k, u(k-1)] - \varepsilon(k) / N_1[w_k, u(k-1)].\end{aligned} \tag{17}$$

The control law (17) consists of the nominal NN controller and uncertainties compensation. The analysis of robustness and stability of the control law (17) is given in [12].

The conceptual structure of the modified AIMNC with control law given by (17) and the NN approximate model given by (10) is shown in Fig. 1. With $S(z^{-1})$ is labeled a set point filter, with $F(z^{-1})$ robustness filter, where z^{-1} is backward shift operator [17]. The role of the blocks marked with "Scale" in Fig. 1. will be explained in the Section III.

D. The modified AIMNC controller design

A positive feature of the IMC control structure is that zero steady-state error in the system can be achieved if we ensure that the steady-state gain of the controller is the inverse value of the steady-state gain of the model [7]. On other hand, it has been shown in [18], that the controller design in the AIMNC structure can be highly facilitated when the reference signal and disturbances have constant values.

Here, we repeat conditions under which it is possible to achieve the satisfactory accuracy in the steady-state with AIMNC structure shown on the Fig. 1. in presence of the constant reference signal and constant disturbances [18]. If the system achieves the zero steady-state error then $y(k) = r(k)$ and $\Delta u(k) = u(k) - u(k-1) = 0$, then using (15) and (17), one has

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

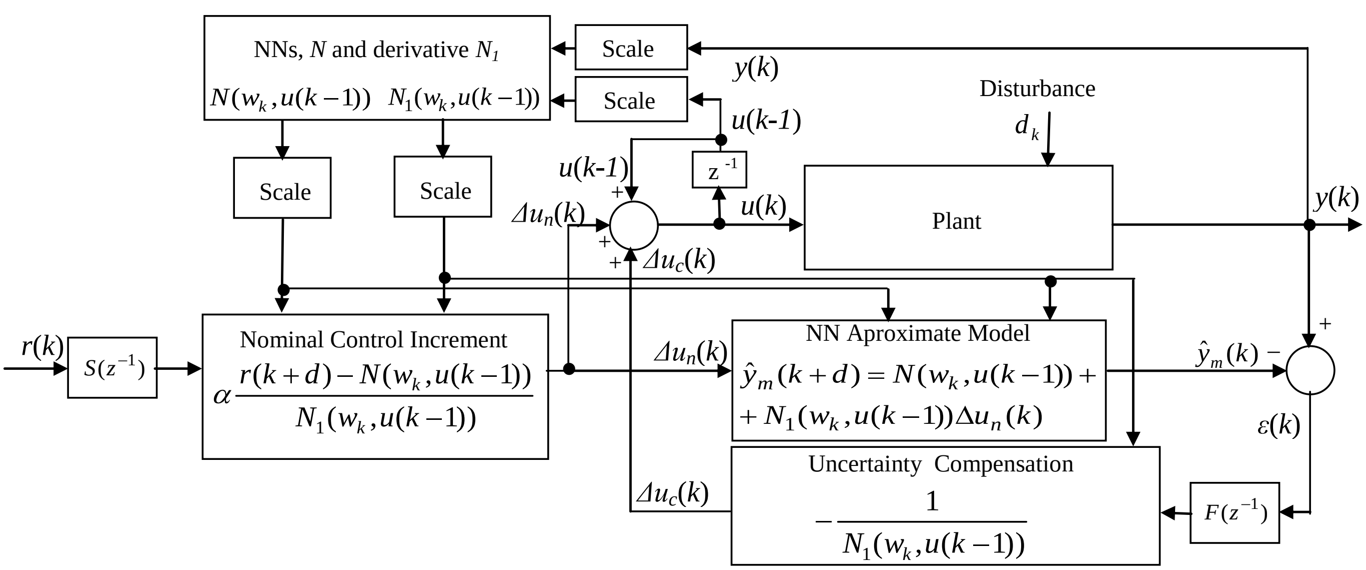

Fig. 1. The conceptual structure of the modified AIMNC

or

$$\alpha r(k+d)-\alpha N[w_k,u(k-1)]-\varepsilon(k)=0,$$

and after substituting (15) in last equation it becomes

$$\alpha r(k+d)-\alpha N[w_k,u(k-1)]-y(k)+\hat{y}_m(k)=0. \quad (18)$$

In the steady-state we have $\hat{y}_m(k)=\hat{y}_m(k+1)=...=\hat{y}_m(k+d)$. Substituting (10) and (13) in to (18), we obtain

$$\alpha r(k+d)-\alpha N[w_k,u(k-1)]-y(k)+N[w_k,u(k-1)] \\ +\alpha(r(k+d)-N[w_k,u(k-1)])=0,$$

or

$$2\alpha(r(k+d)-N[w_k,u(k-1)])=y(k)-N[w_k,u(k-1)],$$

and consequently

$$\alpha=\frac{1}{2}\cdot\frac{y(k)-N[w_k,u(k-1)]}{r(k+d)-N[w_k,u(k-1)]}. \quad (19)$$

Also, when reference values are constant $r(k)=r(k+1)=...=r(k+d)$ the system will have the zero steady-state error if $y(k)=r(k)=r(k+1)=...=r(k+d)$. It follows from (19) that $\alpha=0.5$ is the necessary condition that the system in Fig. 1. attains the zero steady-state error in the case of the constant reference signal and constant disturbances.

The comparison of the AIMNC strategy with respect to performance of the fixed and adaptive IMC has been presented in [18]. Through a sequence of simulations we have demonstrated performance of the AIMNC strategy and verified that the system with the parameter value of $\alpha=0.5$ achieves the zero steady-state error in case of the constant reference signal and constant disturbances.

III. The Modified AIMNC for the Double Tank System

Since most industrial processes have slow dynamics we consider the control design procedure for the nonlinear plant in the cases of such kind of process dynamics. Also, in a large number of industrial processes inputs and outputs of the plant can not take negative values. In addition to that, it is necessary to take into account a downside of the possible actuator saturation.

In order to illustrate the validity of the proposed control design in cases of slow nonlinear discrete time processes we have chosen a double tank system as the plant. Its schematic representation is shown in Fig. 2. It is a nonlinear plant with slow dynamics that is often used for a verification of various control strategies: adaptive IMC [4], neuro-adaptive IMC [9], self-tuning regulator [19], Generalized Predictive Control

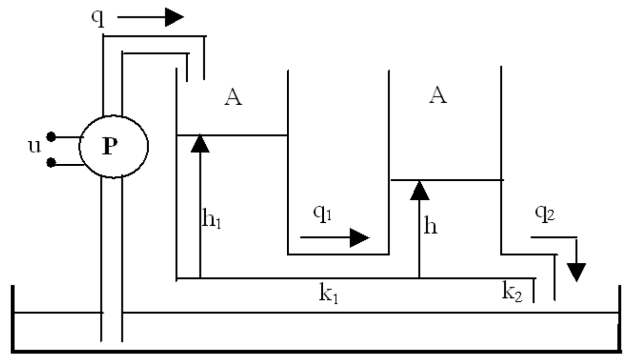

Fig. 2. The schematic representation of the double tank system

(GPC) [20], self-tuning IMC-PID regulator [21], direct control with neural networks [22], swarm adaptive tuning of hybrid PI-NN controller [23], Robust $\mathcal{H}2/\mathcal{H}\infty$/reference model dynamic output-feedback control [24].

The input flow q into the first tank is proportional to the voltage u of the pump P, which is the input to the plant. The fluid flows from the first tank to the second and flow rate q_1 is a function of the difference of liquid level h_1 and h in the first and second tank, respectively. From the second tank the fluid flows freely and a flow q_2 is a function of liquid level h which is the output of the plant. The task of the control system is control of the liquid level $y=h$[m] in the second tank by changing the voltage u[V] at the pump input.

The parameters of the plant, shown in Fig. 2., are: a cross-sectional area of the tank $A=0.0154[\mathrm{m}^2]$, the discharge coefficient of the first tank k_1 and discharge coefficient of the second tank k_2. Based on the balance between changes in the amount of fluids in the tanks and flows we have a system of nonlinear equations [21],[22]:

$$\frac{dh_1}{dt}=\frac{1}{A}\left(ku-k_1\sqrt{2g(h_1-y)}\right), \quad (20)$$

$$\frac{dy}{dt}=\frac{1}{A}\left(k_1\sqrt{2g(h_1-y)}-k_2\sqrt{2gy}\right), \quad (21)$$

where $k=q/u=1.174\cdot10^{-5}[\mathrm{m}^3/\mathrm{Vs}]$ is the coefficient of the pump and $g=9.81[\mathrm{m/s}^2]$ is the acceleration of gravitational force. Since the dynamics of the pump is negligible compared to the dynamics of the two connected tanks, it is presented here as a static gain. The parameters k_1 and k_2 are determined experimentally in a steady state. Let in the steady state magnitudes h_1^0 and y^0 are achieved at a control signal u^0, then $dh_1/dt=dy/dt=0$ and we have

$$u^0=\frac{k_1\sqrt{2g}}{k}\sqrt{\left(h_1^0-y^0\right)}, \quad (22)$$

$$y^0 = \frac{k_1^2}{k_1^2 + k_2^2} h_1^0 . \tag{23}$$

For the experimentally determined values of the parameters one obtains $k_1 = 2{,}46476 \cdot 10^{-5} [\mathrm{m}^2]$ and $k_2 = 1{,}816245 \cdot 10^{-5} [\mathrm{m}^2]$.

Simple forward-difference approximations of the plant model given by (20) and (21) are

$$h_1(k+1) = h_1(k) + \frac{1}{A}\left(ku(k) - k_1\sqrt{2g\left(h_1(k) - y(k)\right)}\right), \tag{24}$$

$$\begin{aligned} &y(k+1) = y(k) + \\ &\frac{1}{A}\left(k_1\sqrt{2g\left(h_1(k) - y(k)\right)} - k_2\sqrt{2g \cdot y(k)}\right) \end{aligned} \tag{25}$$

By entering the above mentioned parameter values of the plant into (24) and (25) we obtain a nonlinear discrete time model of the plant used for the design of the AIMNC controller:

$$\begin{aligned} &h_1(k+1) = h_1(k) + \\ &0.0007625u(k) - 0.0070893\sqrt{h_1(k) - y(k)}, \end{aligned} \tag{26}$$

$$\begin{aligned} &y(k+1) = y(k) + \\ &0.0070893\sqrt{\left(h_1(k) - y(k)\right)} - 0.0052243\sqrt{y(k)}. \end{aligned} \tag{27}$$

In this model it is necessary to include the saturation of the actuator, i.e. the control signal u (the plant input) is in the range of $[0 \quad 10]$ volts. Also, the output y of the plant can not take negative value. The fluid level in the first tank must not exceed the value $h_1 = 0.65[\mathrm{m}]$. From the (23), $h_1^0 / y^0 = 1.543$, the desired stationary value of the plant output must not exceed the value $y^0 = 0.4213[\mathrm{m}]$.

The step response of the double tank system, represented by (26) and (27), for the pump voltage $u = 3.065[\mathrm{V}]$, takes a stationary value of $y = 0.2[\mathrm{m}]$ at the output, Fig. 3. The nonlinear discrete time plant model of double tank system can be approximated by a linear one with a single pole and gain as is given by

$$\tilde{P}_{DTS}(z^{-1}) = \frac{b_1 z^{-1}}{1 - a_1 z^{-1}} = \frac{0.0001893 z^{-1}}{1 - 0.9971 z^{-1}} , \tag{28}$$

This model has a pole at $a_1 = 0.9971$. It has a very slow dynamics, Fig. 3. The system needed over 2000 sample periods to reach a steady state from a zero initial level, by a constant excitation of the pump, whereby a sampling period for a real system is 1 second.

A. A Neural model of the double tank system

The MLNN structure with two hidden layers has been used for modeling of the nonlinear discrete time dynamical system. As inputs of the NN at time instant *k* were $w_k = [y(k)]$ and

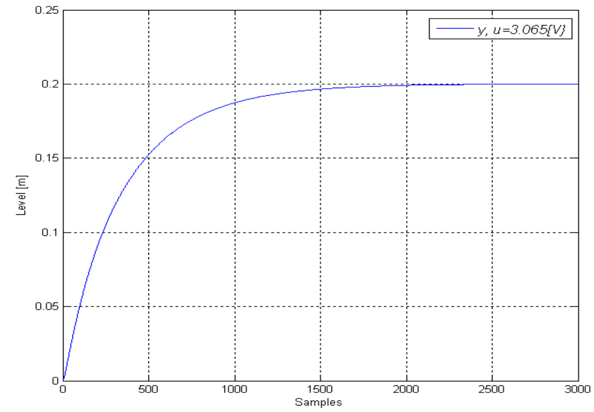

Fig. 3. The step response of the double tank system for pump voltage $u = 3.065[\mathrm{V}]$

$u(k-1)$. The MLNN in the first and second hidden layer has had 10 neurons with hyperbolic tangent activation functions and bias inputs. The linear activation function and bias input has been used for the output neuron.

Since the double tank system have slow dynamics it is necessary to pay special attention to the generation of adequate training set, as well as the scaling of inputs and outputs of a neural network in the training process, and then in the AIMNC structure.

The different types of training sets have been generated for different control vectors. A particular training set consisted of 12.000 pairs composed of $y(k)$ and $u(k-1)$, where each pair represents an input vector of the neural network in time instant *k*. The desired value $y(k+1)$ has been obtained based on (26) and (27).

A very good neural model for the AIMNC structure shown in Fig. 1. was obtained for the control input $u(k), k = 1,\ldots,12000$ chosen as a random number in the range $[0 \quad 8]$ with a mean value 4.0077, and the generated 12.001 values of $y(k)$ were in the range $[0 \quad 0.373]$. Fig. 4. shows the double tank system output $y(k)$ generated by this random control input.

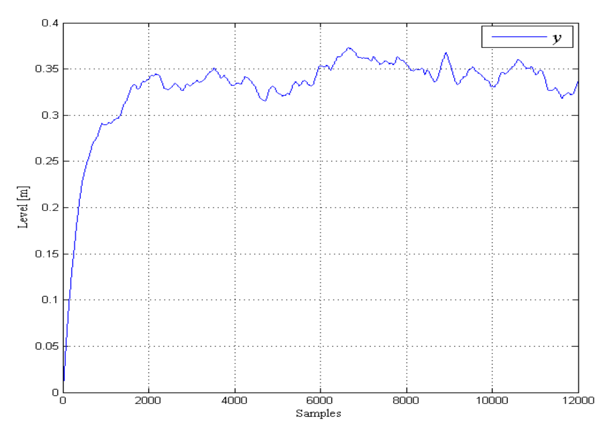

Fig. 4. The double tank system output y for the input vector $u = rand[0 \quad 8][\mathrm{V}]$

A motivation for this choice of training pairs has been derived from a request to regulate the plant output in the range from 0 to 0.35 meters, and therefore it was chosen to change the control signal from 0 to 8 volts with a mean value near to 4. The steady state $y^0 = 0.35[\mathrm{m}]$ corresponds to the voltage $u^0 = 4.0535[\mathrm{V}]$ at the pump input. The initial value of the plant output has been set to $y(1) = 0$. With the proposed selection of training pairs and the initial conditions an opportunity was afforded to observe a plant dynamics contained in a transition process from the zero initial state to the end of the operating range, and in the vicinity of the steady-state.

For the NN training, a MATLAB function "newnarxsp" [25], has been used. The inputs to the MLNN were scaled to the range $[-1, \ 1]$, training algorithm used *Levenberg-Marquart* method [26]-[28], a number of training epochs was 1000 and the achieved mean square error was 4.45x10^{-5}. As a result of off-line training we obtained the matrix $W_{10} = [W_{11} \quad W_{12}]$, $W_{10} \in R^{10\times 2}$, $W_{12} \in R^{10\times 1}$, $W_{21} \in R^{10\times 10}$ and $W_{32} \in R^{1\times 10}$ and vectors b_1, b_2 and b_3, with dimensions 10x1, 10x1 and 1x1, respectively.

The blocks marked with a "Scale" in Fig. 1. are introduced for the reason that the off-line training of MLNN performs scaling of inputs and the output to the desired range $[-1 \ \ 1]$. So to calculate $N[w_k, u(k)]$ in the AIMNC control structure it is necessary to scale inputs within the range $[-1 \ \ 1]$, and the output in the range $[0 \ \ 0.373]$.

Fig. 5. shows the step responses of the neural network $N[y(k), u(k-1)]$ and of the double tank system given by (26) and (27) for the step change of the voltage $u = 3.065[\mathrm{V}]$ at the pump input. The inputs in the neural network were scaled to the range $[-1, \ 1]$, and the output to the range $[0 \ \ 0.373]$. From Fig. 5. is evident that the resulting neural model, with an order of the model error of $10^{-4}[\mathrm{m}]$, is a good model of nonlinear plant at hand. The model error ε_m is shown on Fig. 5, too.

A derivative of the the neural network $N_1[y(k), u(k-1)]$ is shown in Fig. 6. In this case, the derivative of the NN for a modeling of the plant with slow dynamics has an order of 10^{-3}. It appears in the denominator of (13) and (16) for a calculation of the nominal control increment $\Delta u_n(k)$ and control increment for compensation of the model error and disturbances $\Delta u_c(k)$, respectively. For sake of comparison, Fig. 6b. also shows the derivative of the neural network for the modeling of the nonlinear plant with fast dynamics considered in [18].

B. The modified AIMNC controller for the double tank system

In the case of the nonlinear plant with slow dynamics the derivative of the neural network $N_1[y(k), u(k-1)]$ usually takes very small values. When using the AIMNC control structure this could represent a serious problem. The control increment in the control law given by (17) can take unacceptably high values. On the Fig. 7., the reference signal $r = 0.2[\mathrm{m}]$, system output y, NN approximate model output $\hat{y}_m$ and model error ε are shown and on the Fig. 8. the corresponding control action u and control increment Δu in the case of reference signal $r = 0.2[\mathrm{m}]$. From the Fig. 8. it is seen an unacceptable behavior of the AIMNC control structure. The system is practically stable only due to the saturation of the actuator.

The control increments, due to the very small values of derivative of the neural network, are too high and the voltage at the pump oscillates between the saturation limits 0 and 10. It is therefore necessary to consider how it is possible to limit the values of the control increments in order to achieve acceptable system behavior.

An adequate control signal to control systems with slow dynamics, that most of the industrial processes posses, has three distinct segments. Typically, the first segment consists of a step change of the control signal, and the second of its exponential decrease or increase depending on the sign of the reference signal step change. In the case of the positive plant gain, if the step change of the reference signal is positive then the control signal in the second segment is decreasing and vice

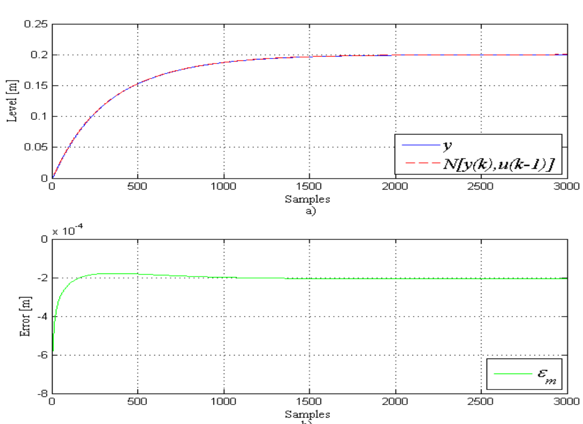

Fig. 5. The neural network $N[\cdot]$ and the double tank system y outputs, and model error ε_m for the step changes of voltage at the pump input

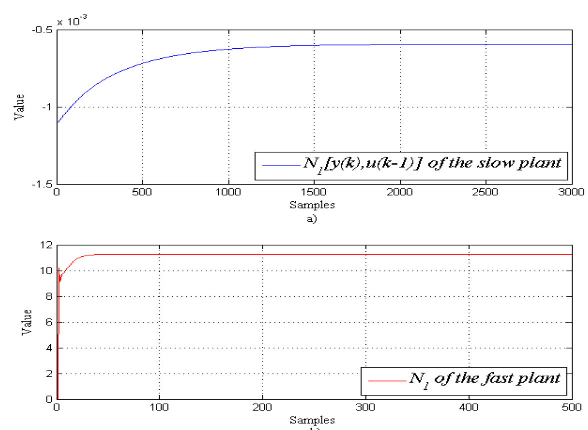

Fig. 6. The derivatives $N_1[\cdot]$ of the NNs of the slow plant and fast plant

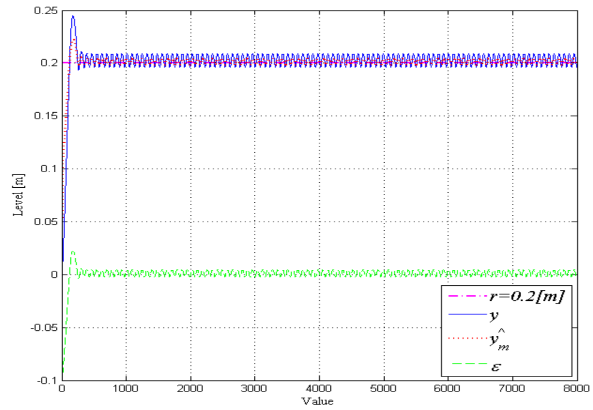

Fig. 7. Reference $r = 0.2[\mathrm{m}]$, system output y, NN approximate model output $\hat{y}_m$ and model error ε

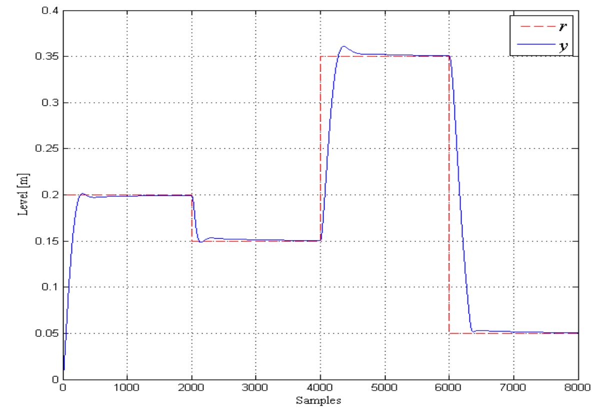

Fig. 9. System output y and reference r

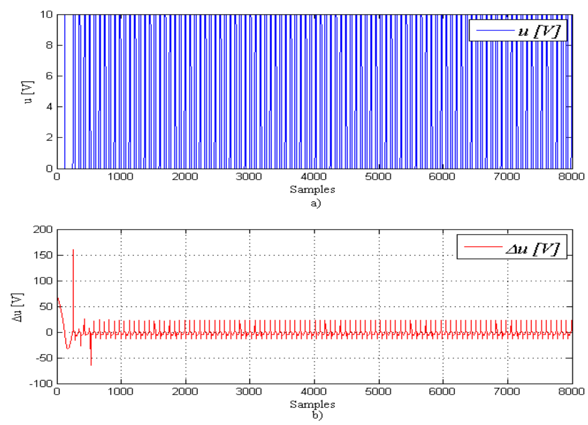

Fig. 8. Control u and control increment Δu for reference $r = 0.2[\mathrm{m}]$

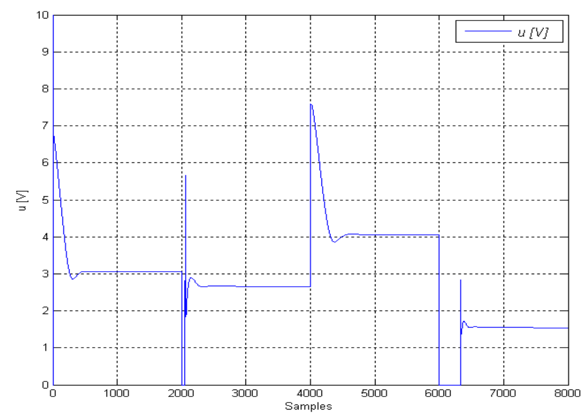

Fig. 10. Control action u

versa. The third segment is with a constant value of the control signal for a fixed reference signal that should provide the zero steady-state error.

It has already been shown that the satisfactory accuracy of the system with the AIMNC controller will be achieved if $\alpha = 0.5$, and we have therefore provided by the proper value of the control signal in the third segment.

A required form of the control signal can be achieved if we ensure that the step change of the reference signal create step change of the neural model output. This requires a different way to scale the control signal that is an input to the neural network, i.e. it is necessary to increase it. Therefore, in the considered case we have scaled the input of the neural model, to the range $[0 \quad 62]$.

We have performed the simulation of the AIMNC strategy shown in Fig. 1. with the obtained MLNN. The set point filter was chosen as $S(z^{-1}) = (1 - r_1)/(1 - r_1 z^{-1})$ with $r_1 = 0$, i.e. $S(z^{-1}) = 1$, and a robustness filter as $F(z^{-1}) = (1 - 0.99942)/(1 - 0.99942 z^{-1})$. Due to the proposed method of the control signal scaling, neural model error became bigger, and we have used the robustness filter $F(z^{-1})$.

The reference $r(k)$ was chosen to take the values of 0.2, 0.15, 0.35, and 0.05, successively for five periods of the 2000 samples.

On the Fig. 9. the response of the system with AIMNC controller for the double tank system with the proposed method of a control signal scaling is shown. The corresponding control signal is shown in Fig. 10.

Figs. 9.-10. depict satisfactory behavior of the proposed modified AIMNC strategy for the typical industrial processes and confirm that the choice of parameter $\alpha = 0.5$ provides the zero steady-state error in cases of the constant reference signals.

IV. Conclusion

In this paper we have presented an improvement of the AIMNC structure. The procedure of designing the MLNN model and controller is shown. The necessary condition for providing an appropriate accuracy of the system at steady state in the case of the constant reference signal and constant disturbances is derived.

Also, we have suggested an approach in which one can ensure satisfactory behavior of the AIMNC law for controling slow industrial processes and provide the zero steady state error in the cases of constant reference signals and constant disturbances. Simulation results confirm performance improvements obtained by the proposed modification of the AIMNC algorithm.

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