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An AIMNC Design Procedure for the Typical Industrial Processes

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Abstract— **In this paper we have discussed how to apply an Approximate Internal Model-based Neural Control (AIMNC) to the typical industrial processes. 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. Selection of training data and an extension of the AIMNC controller for the typical industrial processes are proposed.**

Keywords - artficial neural networks; nonlinear internal model control; process control; training set; zero steady-state error;

I. Introduction

The Internal Model Control (IMC) architecture might be imaged as a system with two degrees of freedom consisting of plant model dynamics and some approximation of the plant model inverse dynamics. The 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 [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]. Furthermore, as Multilayer Neural Networks (MLNNs) have been provided with universal approximation capabilities they were used in IMC architectures to control nonlinear processes [2],[5]-[10]. In that sense the Approximate Internal Model-based Neural Control (AIMNC) was proposed for unknown nonlinear discrete time processes [11]-[13]. Also, high performance of the AIMNC had been demonstrated at applications to the industrial processes [14].

The typical industrial processes usually have a very slow dynamics. The well-known examples of such processes are tanks, where the liquid levels are controlled by using the difference between the input and output flow rates to form a manipulated variable [15]. Since the double tank system has slow dynamics it is necessary to pay a special attention to the control law design procedure which consists of the generation of adequate training set for off-line training of the NN model of plant dynamics and AIMNC controller design. The AIMNC controller design is based on a heuristic consideration of the needed control changes which provide requested tracking performance of the control system. 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 AIMNC controller design are given. The Section III gives an extension of the AIMNC algorithm applied to double tank system together with simulation results demonstrating performance of the proposed control law design procedure in controlling slow processes. In the Section IV we give conclusions of the work.

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 [16]

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

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

In this paper, the MLNN has been used for modeling of nonlinear discrete time dynamic systems. 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 NN model of the nonlinear dynamic system and ξ_k is an model error. The vector of the NN is omitted for simplicity. In the presence of disturbances (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

The NN controller in the IMC control structure represents 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, 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 ([11]-[13])

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

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 $\hat{y}_m(k+d)$ 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), the 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.

C. A controller design

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

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

The control increment in (6) can be divided into two parts $\Delta u(k) = \Delta u_n(k) + \Delta u_c(k)$, where $\Delta u_n(k)$ is the nominal control increment and $\Delta u_c(k)$ is used to compensate the model error and disturbances [12]. When the model is exact and there are no disturbances, i.e. in the nominal case, the NN approximate model is as follows

$$\hat{y}_m(k+d) = N[w_k,u(k-1)] + N_1[w_k,u(k-1)]\Delta u_n(k). \tag{8}$$

If the NN approximate model (8) has a stable inverse, then the nominal control increment $\Delta u_n(k)$ can be calculated as follows

$$\Delta u_n(k) = (r(k+d) - N[w_k,u(k-1)])/N_1[w_k,u(k-1)], \tag{9}$$

where $r(k+d)$ is the reference signal at time instant $(k+d)$.

If the NN approximate model (8) has an unstable inverse, it is needed that (9) should be modified by introducing the parameter α, as proposed in [12], according to

$$\Delta u_n(k) = \alpha(r(k+d) - N[w_k,u(k-1)])/N_1[w_k,u(k-1)], \tag{10}$$

where $0 < \alpha \le 1$. Introduction of the parameter α ensures that the $\Delta u_n(k)$ given by (10) is bounded.

In the presence of the plant model error and disturbances we have

$$\begin{aligned} y(k+d) &= N[w_k,u(k-1)] + N_1[w_k,u(k-1)]\Delta u_n(k) \\ &+ N_1[w_k,u(k-1)]\Delta u_c(k) + R_k + v_k. \end{aligned} \tag{11}$$

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

$$\varepsilon(k) = y(k) - \hat{y}_m(k). \tag{12}$$

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

$$\Delta u_c(k) = -\varepsilon(k)/N_1[w_k,u(k-1)]. \tag{13}$$

Based on (10) and (13) the control law is expressed as

$$\begin{aligned} u(k) &= u(k-1) + \alpha(r(k+d) - N[w_k,u(k-1)]) \\ &/N_1[w_k,u(k-1)] - \varepsilon(k)/N_1[w_k,u(k-1)]. \end{aligned} \tag{14}$$

The control law (14) consists of the nominal NN controller and uncertainties compensation. An analysis of robustness and stability of the control law (14) is given in [12].

The conceptual structure of the AIMNC with the control law given by (14) and NN approximate model given by (8) is shown in Fig. 1. With $S(z^{-1})$ is labeled 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 AIMNC controller with zeor steady-state error

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]:

$$\alpha = \frac{1}{2} \cdot \frac{y(k) - N[w_k,u(k-1)]}{r(k+d) - N[w_k,u(k-1)]}. \tag{15}$$

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 (15) 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. A comparison of the AIMNC with respect to performance of the fixed and adaptive IMC has been presented in [18].

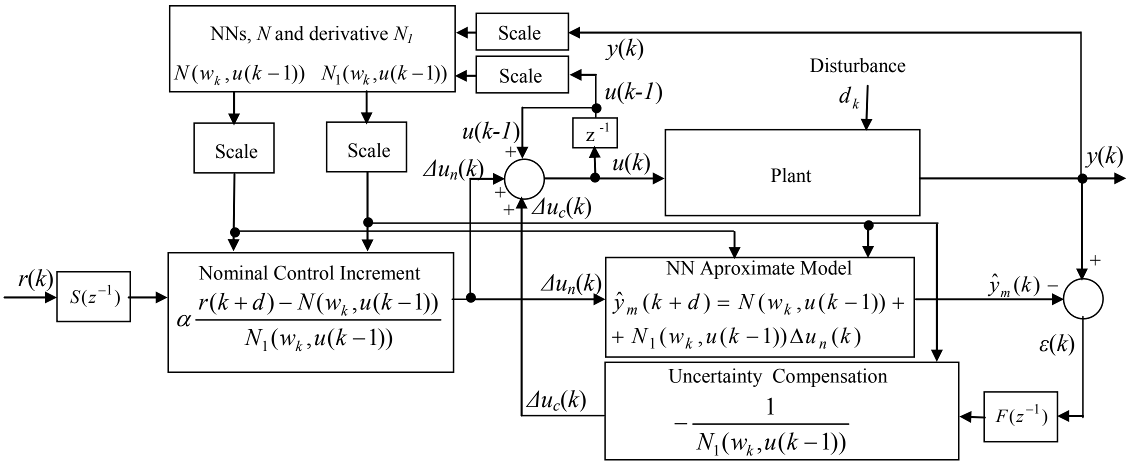

Figure 1. The conceptual structure of the AIMNC

III. THE AIMNC FOR THE DOUBLE TANK SYSTEM

In order to illustrate the validity of the proposed control law design in cases of slow nonlinear discrete time processes we have chosen a double tank system as the plant (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 IMC-PID regulator [19], direct control with neural networks [20], swarm adaptive tuning of hybrid PI-NN controller [21], robust $\mathcal{H}2/\mathcal{H}\infty$/reference model dynamic output-feedback control [22].

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 its 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 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 $y = h$ by changing the voltage u at the pump input. The parameters of the plant, shown in Fig. 2., are: a cross-sectional area of the tank $A = 0.0154$ 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 system of nonlinear equations [19],[20]:

$$\frac{dh_1}{dt} = \frac{1}{A}\left(ku - k_1\sqrt{2g(h_1 - y)}\right), \tag{16}$$

$$\frac{dy}{dt} = \frac{1}{A}\left(k_1\sqrt{2g(h_1 - y)} - k_2\sqrt{2gy}\right), \tag{17}$$

where $k = q/u = 1.174 \cdot 10^{-5}$ m^3/Vs is the coefficient of the pump and $g = 9.81$ 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 $k_1 = 2{,}46476 \cdot 10^{-5}$ m^2 and $k_2 = 1{,}816245 \cdot 10^{-5}$ m^2 are determined experimentally in steady-state conditions [14]. Simple forward difference approximations of the plant model given by (16) and (17) and entering the above mentioned parameter values we obtain a nonlinear discrete time model of the plant used for the design of the AIMNC

$$h_1(k+1) = h_1(k) + 0.0007625u(k) - 0.0070893\sqrt{h_1(k) - y(k)}, \tag{18}$$

$$y(k+1) = y(k) + 0.0070893\sqrt{(h_1(k) - y(k))} - 0.0052243\sqrt{y(k)}. \tag{19}$$

In this model it is necessary to include the saturation of the actuator, i.e. the control signal u is in the range of $[0 \;\; 10]$ volts. Also, the output y of the plant can not take negative values. The fluid level in the first tank and the plant output must not exceed the values $h_1 = 0.65$ m and $y^0 = 0.4213$ m, respectively.

A. *An adequate training set for the NN model of the double tank system*

The MLNN structure with two hidden layers has been used for modeling of the nonlinear discrete time dynamic system. As inputs of the NN at time instant *k* were $w_k = [y(k)]$ and $u(k-1)$. 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 has slow dynamics it is necessary to pay attention to the generation of adequate training set, as well as the scaling of inputs and outputs of the NN in the training process, and then in the AIMNC structure. Training data set has direct and decisive influence on the supervised learning of NN, which is chiefly manifested in

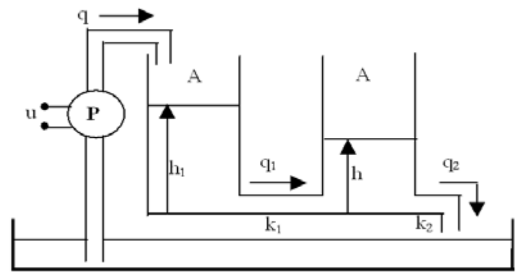

Fig. 2. The schematic representation of the double tank system

generalization ability, learning time and accuracy. High quality of training data set can bring high performance of NN [23]. If the NN receives an input that is outside of the range covered in the training data, then the NN response will always be unreliable. There is little we can do to improve the NN performance outside the range of the training data [24].

The different types of training sets have been generated. 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 NN in time instant *k*. The desired value $y(k+1)$ has been obtained based on (18) and (19). A very good NN model for the AIMNC structure shown in Fig. 1., was obtained for the control input $u(k), k=1,...,12000$ 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. 3. shows the double tank system output $y(k)$ generated by this random control input. We want 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 $y^0 = 0.35$ m corresponds to the pump voltage $u^0 = 4.0535$ V. The initial value of the plant output has been set to $y(1)=0$. With proposed selection of training pairs and the initial conditions an opportunity was afforded to observe the 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 [25].

Also, we generated the following input vectors for off-line training of the NN model:

a) $u_a = rand[0 \quad 6.2]$ V, $y(1)=0$, $y^0 = 0.2$ m

b) u_b has been generated as random value that does not change for the 200 samples,

c) u_c are the sums of given constant values during 3,000 samples and randomly generated values in the range $[-0.5 \quad 0.5]$,

d) u_d took values of 2.6540, 4.0535, 0.0500 and 3.4260 respectively. For each given value u_d a sequence of 3,000 constant samples were generated.

Fig. 3. shows vector $y(k)$ for the input vector u_a. Fig. 4. shows vector $y(k)$ for the input vectors u_b, u_c and u_d.

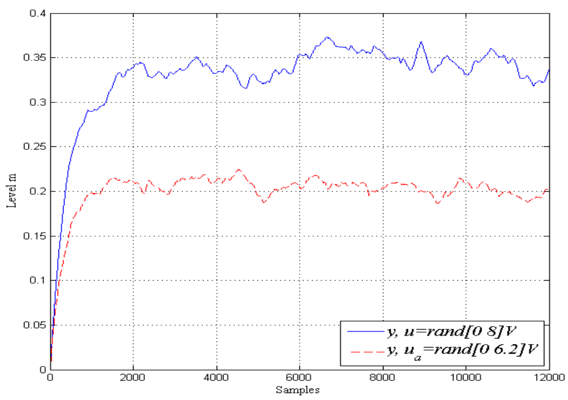

Fig. 3. The double tank system output y for the input vectors $u = rand[0 \quad 8]$ V and $u_a = rand[0 \quad 6.2]$ V

In the NN training, a MATLAB function "newnarxsp" [26], has been used. The inputs to the NN were scaled to the range $[-1, \quad 1]$, training algorithm used *Levenberg-Marquart* method [27]-[29], a number of training epochs was 1,000 and the achieved mean square error was 4.45x10^{-5}. The blocks marked with a "Scale" in Fig. 1. are introduced for the reason that the off-line training of the MLNN 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 control structure it is necessary to scale inputs within the range $[-1 \quad 1]$, and the output in the range $[0 \quad 0.373]$.

For the NN models obtained by different training sets Fig. 5. show modeling errors ε_m of the double tank system for the step change of the voltage $u = 3.065$ V at the pump input, which corresponds to a stationary value of output $y = 0.2$ m. From Fig. 5. it is evident that the NN model obtained with training set generated by input $u = rand[0 \quad 8]$ V is the best. Values of the Mean Square Error (MSE) of the NN models, for different inputs, are given in the Table I.

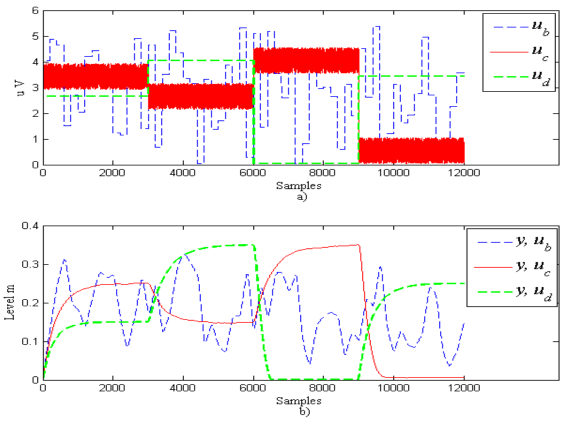

Fig. 4. a) The inputs vectors u_b, u_c *and* u_d, b) The double tank system outputs y for the inputs vectors u_b, u_c *and* u_d

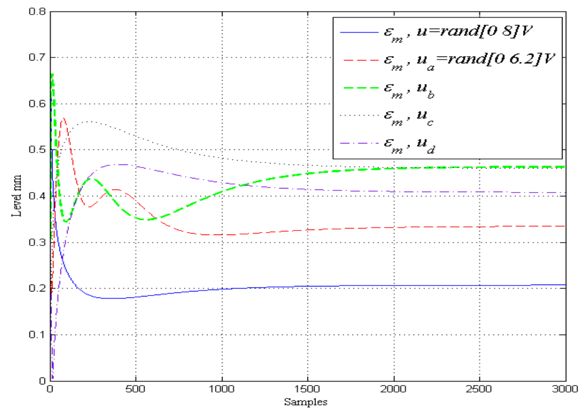

Fig. 5. The NN model errors ε_m for the step changes of the voltage $u = 3.065$ V at the pump, for the different input vectors

TABLE I. MSE OF THE NN MODELS WITH DIFFERENT TRAINING SETS

Control vector	u=[0 8] V	u_a	u_b	u_c	u_d
MSE mm^2	0.042	0.12	0.18	0.23	0.17

B. The AIMNC controller for the double tank system

The NN model obtained with training set generated by the control input $u = rand[0 \quad 8]$ V is used for AIMNC design.

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 (14) can take unacceptably high values. A derivative of the selected NN i.e. $N_1[y(k), u(k-1)]$ 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}. For comparison, Fig. 6b. shows the derivative of the NN model of the nonlinear plant with fast dynamics considered in [18].

On the Fig. 7., the reference signal $r = 0.2$ m, system output y, NN approximate model output $\hat{y}_m$ and model error ε are shown. Fig. 8. shows the corresponding control action u and control increment Δu in the case of reference signal $r = 0.2$ 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 NN, are too high and the voltage at the pump oscillates

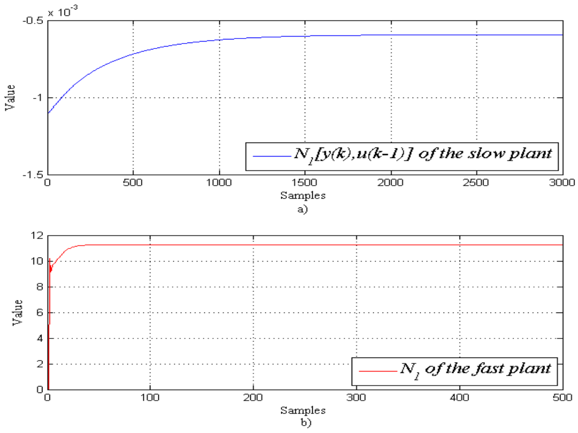

Fig. 6. The derivatives $N_1[\cdot]$ of the NNs of the slow plant and fast plant

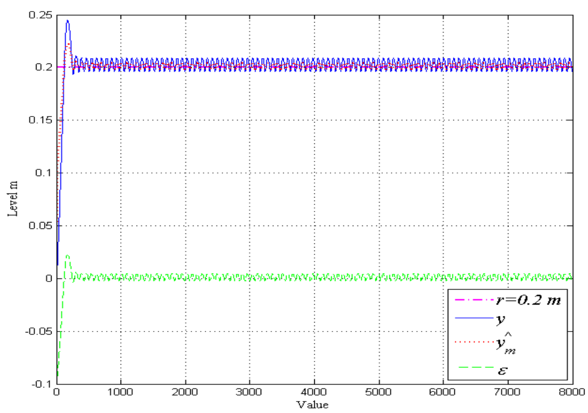

Fig. 7. Reference $r = 0.2$ m, system output y, NN approximate model output $\hat{y}_m$ and model error ε

between the 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 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 versa. The third segment is with a constant value of the control signal for a fixed reference signal that should provide 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 changes of the reference signal create step changes 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 the 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 zero steady-state error in cases of the constant reference signals.

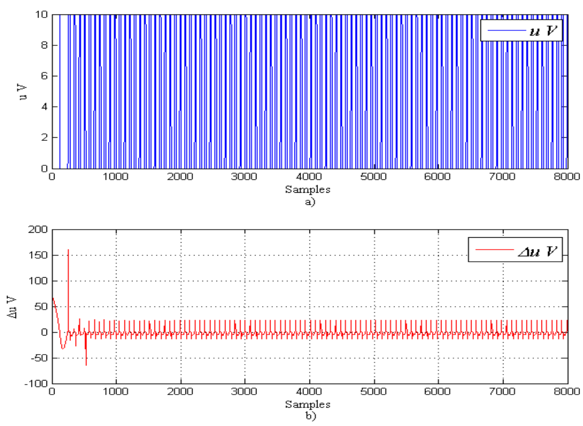

Fig. 8. Control u and control increment Δu for reference $r = 0.2$ m

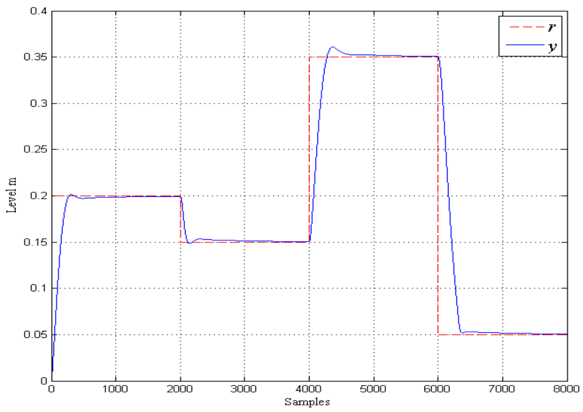

Fig. 9. System output y and reference r

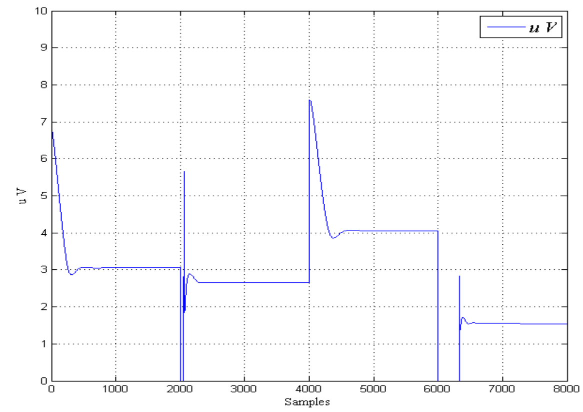

Fig. 10. Control action u

IV. CONCLUSION

In this paper we have presented an AIMNC control law design procedure for the processes with slow dynamics. The procedure of designing the MLNN model and controller is shown. We have suggested an approach of appropriate NN inputs scalling by which one can ensure satisfactory behavior of the AIMNC law to controling slow industrial processes and providing zero steady-state error in the cases of constant reference signals and constant disturbances. Simulation results confirm high performance obtained by the proposed control law design procedure.

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