MINIMIZATION OF ACTUATOR REPOSITIONING USING NEURAL NETWORKS WITH APPLICATION IN NONLINEAR HVAC[1] SYSTEMS

M. J. Yazdanpanah*, E. Semsar†, C. Lucas‡
*yazdan@ut.ac.ir, †semsar@chamran.ut.ac.ir, ‡lucas@ipm.ir
Control & Intelligent Processing Center of Excellence & Department of Electrical and Computer Engineering, University of Tehran, P.O. Box 14395/515, Tehran, IRAN.
Fax: (+98-21) 633029

Keywords: Neural Network, PID Controller, Chopper, Bilinear model, Radial Basis Function (RBF).

Abstract

In process control the main goal is not only the output tracking but also the design of a suitable control signal. It is due to the fact that it is dealt with the actuator's performance directly. This means that the undesired oscillations should be removed to alleviate the malfunction of actuators. More than this, saving energy is an important point in energy-consuming systems such as Heating, Ventilating and Air Conditioning (HVAC) systems. In this paper, a nonlinear saturating element is designed with the help of neural networks. This element chops the undesired oscillations of the control signal. The performance of the system is guaranteed by the use of a number of PID controllers as central controllers and implementation of a performance measurement index to reduce the error between the outputs and desired input signals. A multi-layer perceptron network is used and trained with Error Back Propagation algorithm. The method is applied to a nonlinear model of an HVAC system, which demonstrates the good performance of the proposed design method.

Nomenclature

h_w	Enthalpy of liquid water
W_o	Humidity ratio of outdoor air
h_{fg}	Enthalpy of water vapor
V_{he}	Volume of heat exchanger
W_s	Humidity ratio of supply air
W_3	Humidity ratio of thermal space
C_p	Specific heat of air
T_o	Temperature of outdoor air
M_o	Moisture load
Q_o	Sensible heat load
T_2	Temperature of supply air
T_3	Temperature of thermal space
V_s	Volume of thermal space
ρ	Air mass density
f	Volumetric flow rate of air
gpm	Flow rate of chilled water

1 Introduction

Although in most control designs, output tracking is almost the main goal of the designers, but it is important to notice that having a smooth control signal is as important as output tracking. The reason is that, control signal is usually implemented through the actuators directly, so if it has a lot of overshoots and oscillations, the actuators would be damaged very soon and this is not economical from an industrial view point. More than this saving energy is an important point in energy-consuming systems. For example HVAC systems consume about 50% of the total energy used in the world [8]. In this way if the control strategy could gain at all the goals of tracking, energy saving and minimum actuator repositioning with a level of tradeoff between them, the benefits mentioned above can be achieved simultaneously. Although these are important problems in control applications, the authors didn't find significant researches in this field and the only works encountered are as follow: In [17] an optimal controller is designed by the definition of a cost function in such a way that minimizes the control signal oscillations. The H_∞ method is used in [9,10,18] to minimize the actuator repositioning. The Neural Networks are used for this purpose in [20] and applied to the linear model of an HVAC system. In [6] a neural network is used as a central controller for the purposes of output tracking and oscillation canceling. Internal model control is also applied in [7] to achieve these goals.

In this paper a new method is introduced by the use of Neural Networks. In spite of previous methods, which use Neural Network as a central controller, in this paper the Central controllers are two PIDs and two Neural Networks are used for other control purposes. The purpose of using such a configuration is that: In the industrial applications, the PID is usually the most common choice for process control and this choice is for some reasons such as: its simple tuning, easy hardware implementation and acceptable performance. But as we know, this controller fails in some situations and so it could not satisfy some desirable indices. So if some way could be found to overcome the undesirable properties

[1]Heating, Ventilating and Air Conditioning

$W_o = .0018\ lb/lb$	$C_p = .24\ Btu/lb.°F$	$V_s = 58464\ ft^3$ $V_{he} = 60.75\ ft^3$
$W_s = .007\ lb/lb$	$\rho = .074\ lb/ft^3$	$T_o = 85°F$
$M_o = 166.06\ lb/hr$	$\tau = .008\ hr, k = 5$	$Q_o = 289897$

Table 1: Numerical values for system parameters

without changing the structure of the controller then the benefits of this controller can be maintained and at the same time a good control performance can be achieved. The proposed method in this paper has the aim to overcome the oscillatory response of PID controllers by the insight to good tracking. This method is based upon design of a nonlinear element, which chop the undesired oscillations. Accordingly, a performance index is introduced to achieve an acceptable output signal and minimize the control signal's oscillations. This index is used for the training of the network too, such that when the network is trained, both goals of output tracking and oscillation cancellation will be achieved. This element is placed in feed-forward path and the training is done on-line. Because of the property of Neural Networks, that process information in context and not singly [4], they can receive at a better response in presence of the plant's uncertainties and disturbances. As mentioned above two PIDs are used as the central controllers and their gains are tuned by conventional methods. Neural Networks are trained on-line by Error Back-Propagation (EBP) algorithm. The organization of the paper is as follows: In section 2 the analytical model of the system is brought. Section 3 declares the control problem and the block diagram of the system. In sections 4 and 5, design of PID and nonlinear element are explained. Section 6 discusses the Neural Network structure and in section 7, advantages of the new method and especially the property of reduction of control signal's energy is inspected. Section 8 presents the simulations for an HVAC system. Finally the conclusions are given in section 9.

2 HVAC Model

Several models have been considered for HVAC systems in different references. For example in [9,6] a linear first order model of the system with a time delay is considered which is a common simplified model of the system. In [12,13,14] a nonlinear SISO model is used for simulations. In some other works a bilinear model is considered for controlling either the temperature [11] or both the humidity and temperature [8] which accordingly results in a SISO or a MIMO control problem. In this paper the last case is considered, as it seems to present more practical model of a single-zone Variable Air Volume (VAV) HVAC system. This system is an inherent time-delayed system, which is mostly linearized as first order with a time delay system. More than this, it is a MIMO system in which one of the I/O channel has a right half plane zero, which means it is a non-min-phase system. The HVAC system mathematical relations are as follow [8]:

$$\begin{cases} \dot{x}_1 = u_1\alpha_1 60(x_3 - x_1) - u_1\alpha_2 60(W_s - x_2) \\ +\alpha_3(Q_o - h_{fg}M_o) \\ \dot{x}_2 = u_1\alpha_1 60(W_s - x_2) + \alpha_4 M_o \\ \dot{x}_3 = u_1\beta_1 60(-x_3 + x_1) - u_1\beta_1 15(T_o - x_1) \\ u_1\beta_3 60(.25W_o + .75x_2 - W_s) - 6000u \end{cases}$$

$$y_1 = x_1\ ,\ y_2 = x_2 \qquad (1)$$

Lets define some parameters as bellow:

$$u_1 = f, u_2 = gpm, x_1 = T_3, x_2 = W_3, x_3 = T_2$$

$$\alpha_1 = 1/V_s, \alpha_2 = h_{fg}/C_pV_s, \alpha_3 = 1/\rho C_pV_s, \alpha_4 = 1/\rho V_s,$$

$$\beta_1 = 1/V_{he}, \beta_2 = 1/\rho C_pV_{he}, \beta_3 = h_w/C_pV_{he}$$

In which the variables are defined in nomenclature and the numerical values are as in table 1. In the model brought in [8], the actuator's transfer function is not considered but here in simulations it is used as well. In [12] it is shown that the actuator's transfer function, here a valve, can be assumed as:

$$G_{act}(s) = k/(1+\tau s) \qquad (2)$$

In which k and τ are the actuator's gain and time constant and their values are as in table 1.

3 Problem Statement

Fig. 1 shows the block diagram of the control system in the problem of minimizing the control signal's oscillation. As seen, the system consists of a central controller which itself consists of two PIDs and their gains will be defined in section 4 by conventional tuning methods. Then two blocks of H-LIMITTER can be seen. H-LIMITTER is a nonlinear element and will be described in section 5. This element has two parameters, R, θ , which are the slope and region of saturation function for chopping undesired oscillations respectively. If the value of the input to this element exceed a desired value $R + b$, b is a constant, the nonlinear element chops the input signal, and in this way, a smooth output signal can be achieved by the use of this element in feed-forward path.

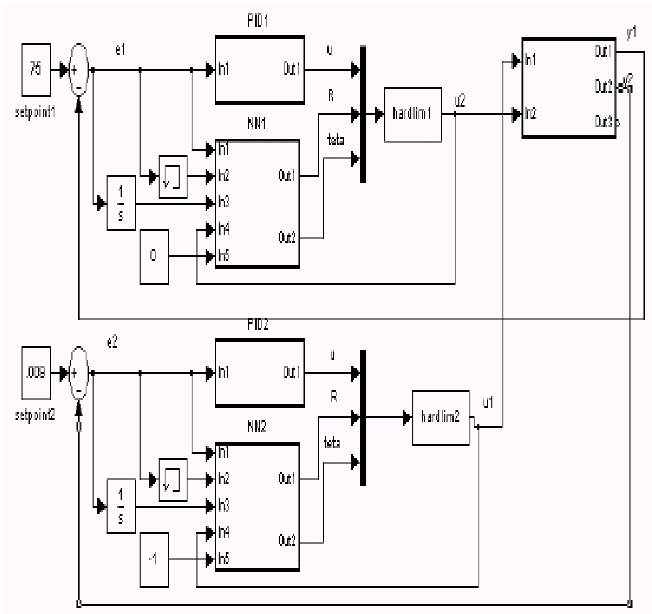

Figure 1: Block diagram of the MIMO Control System

Other elements in Fig. 1 are Neural Networks (NN1, NN2), which have 5 inputs and two outputs and are used in two places for chopping the 2 control signals used as inputs to the system. The inputs to these networks are tracking error $e_i(t), e_i(t-1)$ and its time integral $\int e_i(t)dt$, control signal u_i, which is applied to the plant directly and a constant that can be either 0 or -1. The outputs of the Neural Networks are R,θ. Finally the plant is seen in the figure which was described in section 2. In training the Neural Network, a cost function J, is used which is a measure of the system performance and is described as below:

$$J_i = \frac{1}{2}[k_1 e_i^2 + k_2(\Delta u_i)^2]$$

$$e_i = y_{di} - y_i,\ \Delta u_i = u_i(k) - u_i(k-1) \qquad (3)$$

In which $i = 1,2$ is the number of inputs, k_1 and k_2 are design parameters and the goal is to minimize J_i. As it is obvious, using a nonlinear element in control loop would make the system's response undesirable. To solve this problem, a term e_i^2 is considered in cost function to achieve output tracking and the term Δu_i^2 reduces the control signal's oscillation. In this way by reduction of e_i, the output response would be controlled and by minimization of Δu_i, the rate of variation of u_i would be decreased. In other words, by design of nonlinear elements in such a way which minimize this cost function, the initial goals of the problem are achieved

4 Design of Central Controller

As said before the HVAC plant can be considered as a first order with a time delay system, so by usual methods such as "Process-Reaction Curve" [12], the parameters of such an approximation can be calculated according to the step response of each I/O channel. When the system is identified the PID controller can be tuned with conventional methods described in [16,1,12] and are mentioned in the following sections. It is important to notice that plant considered here is MIMO, but it has some properties, which can be used for designing the individual controllers for two I/O channels. The linear model of the system, calculated by Matlab software, results in 4 I/O transfer functions described by $g_{ij}, i, j = 1,2$ and it can be seen that:

DC gain for $g_{11} = -.0062$

DC gain for $g_{12} = -.0000022$

DC gain for $g_{21} = -97022$

DC gain for $g_{22} = 0$

As it is obvious the second output is affected only by the first input because $g_{22} = 0$ and the first output is affected by both inputs. But the first input has a very small dc-gain. So it's effect is so much weaker than the second output ($g_{11}/g_{21} \approx 10e-7$) and it is acceptable to use the first input for controlling the second output and vice versa. In this way the central controller can be written as:

$$C = \begin{bmatrix} 0 & c_{12} \\ c_{21} & 0 \end{bmatrix} \qquad (4)$$

and c_{ij} is the controller between the ith set point error and jth output [15]. The relationship for each PID is as follows:

$$u = k_p e(t) + k_I \int e(t)dt + k_d \dot{e}(t) \qquad (5)$$

In this paper, the gains are designed by Cohen-Coon method, which results in almost the best response. Here three different methods are mentioned for PID gain tuning.

4.1 Ziegler-Nichols Method

This is one of the most common methods for the design of PID gains used in recent years, but the most problem with this method is the undesired overshoots, appearing in the output response. In [16,1,12] the tables for the gains calculation are available.

4.2 Cohen-Coon Method

This method, similar to Ziegler-Nichols method, causes overshoots in the output response. For more details refer to [1,12].

4.3 Internal Model Control Method

This method was introduced in about 1980 and is almost a new method. The response's speed is increased in this method [5]. The other tuning methods that can be mentioned are Haalman and Pole Placement [1].

5 Design of nonlinear chopper

The input-output characteristic of nonlinear element is seen in Fig. 2. The input to this element is the control signal, which is produced by PID controller. Its output is the control signal, which is applied to the plant directly. $R+b$ and $\theta + a$ are the values of saturation point and slope for the nonlinear element to be designed by the Neural Network. Implementation of this element results in chopping the undesired oscillations of the control signal. The input-output relation of this element is defined as below, in which a,b are constants and R,θ are to be designed on line:

$$y(t) = \begin{cases} u(t)\tan(\theta + a) & |u(t)| < R+b \\ (R+b)\tan(\theta + a) & |u(t)| > R+b \end{cases} \qquad (6)$$

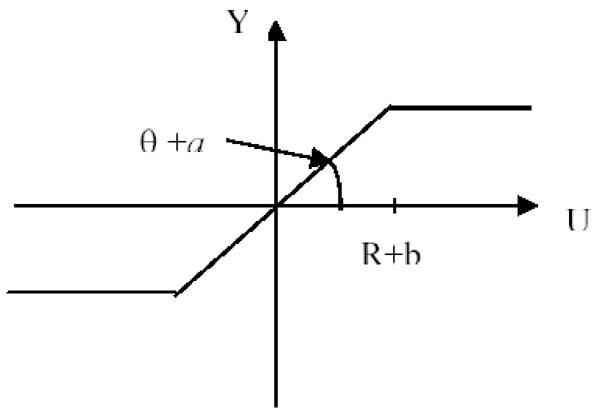

Figure 2: Nonlinear Element Characteristic

6 Design of Neural Network

The Neural Network considered here, is a three-layer perceptron with a hidden layer, which has two neurons in hidden and output layers and 5 neurons in the input layer. Activation functions for the first and second layers ($f_1(x)$, $f_2(x)$ respectively) are radial basis functions for NN1 and sigmoid for NN2 and their relations are as in Equations (7-a) and (7-b):

$$f_1(x) = m_0 \exp(-cx^2) \text{ or } f_1(x) = m_0 \frac{1 - z\exp(-cx)}{1 + z\exp(-cx)} \quad \text{(7-a)}$$

$$f_2(x) = n_0 \exp(-cx^2) \text{ or } f_2(x) = \frac{n_0}{1 + z\exp(-cx)} \quad \text{(7-b)}$$

In Equations (7-a) and (7-b), n_0 and m_0 are parameters to be designed, which can be varied to achieve an optimum response. For initial weighting, the following 3-stage so-called Nguyen-Widrow algorithm is used [2]:

Step 1: β parameter is defined as follows:

$$\beta = .7(p)^{\frac{1}{n}} \quad (8)$$

In which n and p are the number of neurons of the input and output layers.

Step 2: For each hidden layer i , the weights between input and hidden layer $W_{ij}\,(j = 1,...,p)$ are chosen values between -.5 and .5 and by calculation of $\|W_j\|$ the updated weights can be calculated as follows:

$$W_{ij} = \beta \frac{W_{ij}(old)}{\|W_j(old)\|} \quad (9)$$

Step 3: The weights between hidden and output layers are random values chosen between $-\beta$ and β .

6.1 Error Back-Propagation algorithm

The learning algorithm used here, is EBP and the optimization idea of steepest descent is used [3]. If input and output weights are considered as W_{ij} and V_{jk} then the following equations for updating the weights are valid in which Δu is discrete derivative of control signal, η is the rate of learning, X_j and z_k are outputs of the first and second layers respectively. I_i stands for the i th input to the network, f_1', f_2' .are the derivatives of first and second layer activation functions and $\frac{\partial u}{\partial z_k}$ is the derivative of control signal with respect to the network outputs. This term can be considered according to the nonlinear element characteristic or only by its sign. n, m, h are the number of neurons in the input, hidden and output layers correspondingly.

$$\Delta W_{ij} = -\eta \frac{\partial J}{\partial W_{ij}} = -\eta \frac{\partial u}{\partial W_{ij}} \times (-k_1 e \frac{\partial y}{\partial u} + k_2 \Delta u),$$

$$\frac{\partial u}{\partial W_{ij}} = \sum_{k=1}^{h} f_1'(j) f_2'(k) V_{jk} I_i \frac{\partial u}{\partial z_k}$$

$$X_j = f_1(\sum_{i=1}^{n} W_{ij} I_i), \; z_k = f_2(\sum_{j=1}^{m} V_{jk} X_j)$$

$$\Delta V_{jk} = -\eta X_j f_2'(k)(-k_1 e \frac{\partial y}{\partial u} + k_2 \Delta u) \frac{\partial u}{\partial z_k} \quad (10)$$

7 Properties of the Proposed Controller

This controller has a good and almost fast response to the input because of the power of Neural Networks in case of the system's uncertainties. It means that when PID can't show a good performance because of the uncertainties and lack of knowledge of the system's dynamics, the Neural Network can help it to achieve a good performance. The most important property of this controller is the control signal's oscillations canceling, which was mentioned in previous sections. Moreover, the method reduces the total energy of the control signal, which will be discussed in next section.

7.1 Energy Reduction

By the use of this method as well as achieving the above control goals, the control signal's energy is reduced too. This can be reasonable, since by canceling the undesired oscillations of the control signal, the energy can be used in a useful way and its losses can be reduced, so though using less energy, better performance can be gained. Related numerical results are brought in simulations and two indices are proposed for comparing the control signal energy between PID and the introduced method: The numerical values for indices 1 and 2 show the property of energy saving of the introduced method

$$\text{a. } E_1 = \int_0^t (u - u_{eq})^2 \, dt \quad (11)$$

in which u_{eq} is the control signal value in steady state.

$$\text{b. } E_2 = \int_0^t (\Delta u)^2 \, dt = \int_0^t (u(t) - u(t-1))^2 \, dt \quad (12)$$

8 Simulations

Simulations presented here, are the results of applying the proposed method on a nonlinear model of an HVAC system. In these systems, control signal is applied to the actuators directly. As an example, consider the valve for control of the hot or cold water, or the volumetric flow rate of air. The main problem with these actuators, are their damages because of the undesired oscillations applied to them [19]. In this way, using this new method on an HVAC system, is a good measure for examining the quality of the new method. In figures 3,4,5 and 6 a comparison is made between the output and control signals result in by conventional control designs, which only use the PID controllers and the proposed method in this paper. The trajectory to be tracked is a quintic trajectory which get at it's final value in .5 time base (It can be called a soft step with .5 (t.b.) time constant). The set points for two outputs are as $75°F$ and .009 lb/lb for the space temperature and moisture percentage. As seen in Fig. 3, the transient oscillations of the output responses have been reduced significantly. More than this control signal in Fig. 6 has reduced number of oscillations in comparison with PID. In figures 4 and 5 the second output and its correspondence input signal are seen. In this case as the original signals didn't contain many oscillations so the limitter doesn't need to chop them, but the H-Limitter increases the response speed and reduce the value of the response peak. In figures 7 and 8 the response and control signal of the system to a square waveform for the first output is seen. As it is obvious after one period the number and peak value of overshoots and undershoots reduces. In figures 9-10 the two indices introduced for control signal energy are brought for second input. As seen besides the good performance of the proposed method, the energy of the control signal is reduced significantly in comparison with PID control. The PID gains for an HVAC system are brought in tables 2,3. These values are for a linear system of the differential equations described in Equation (1), designed by Ziegler-Nichols and Cohen-Coon methods [6]. The values of a and b in nonlinear elements are chosen to be zero for b in two limitter blocks and .134, .046 for a.

Also the final value for R,θ are as .75, .74 for first limitter and 1.5, 1.5 for second limitter.

The design parameters of Neural Networks are as $\eta=.1, k_1=.1, k_2=.12, n_0=.75, m_0=3, z=1, c=.81$ and $\eta=.81, k_1=k_2=.1, n_0=3, m_0=9, z=1, c=.01$ for two networks respectively. The values of two indices introduced for energy are reduced by 45%, 13% respectively by the help of new introduced method.

9 Conclusions

In this paper, a nonlinear element was designed in order to chop the undesirable oscillations of the control signal. A perceptron Neural Network, EBP training algorithm and RBF activation functions were used for this purpose. This design method was applied to a nonlinear model of an HVAC system and reached to the pre-specified goals of design such as output tracking and reduction of control signal's oscillations, which are apparent in simulations. Moreover, the total energy of the control signal was considerably reduced by this method.

References

[1] K. Astrom, T. Hagglund. "PID controllers: theory, design and tuning", ISA, (1995).

[2] L. Fausett. "Fundamentals of neural networks", Prentice Hall, (1994).

[3] S. Haykin. "Neural networks: a comprehensive foundation", Macmillan College Publishing, (1999).

[4] M.B. Menhaj. "Fundamentals of neural networks", (in Farsi), Prof. Hessabi Publication, (1998).

[5] M. Morari, E. Zafiriou. "Robust process control", Prentice Hall, (1989).

[6] M.R. Omidi. "Minimization of control signal oscillations in HVAC systems", (in Farsi), M.S. Thesis, University of Tehran, (2000).

[7] M.R. Omidi, M.J. Yazdanpanah. "Minimization of actuator repositioning using Internal Model Control", Fourth Portougues' Automatic Control Conf., (2000).

[8] B.A. Serrano, M. Velez-Reyes. "Nonlinear control of a Heating, Ventilating and Air Conditioning system with thermal load estimation", *IEEE Trans. on Control Systems Tech*., **Volume** 7, No. 1, (1999).

[9] M. Tavanaii. "Achieving optimal and robust performance in HVAC systems", (in Farsi), M.S. Thesis, University of Tehran, (2000).

[10] M. Tavanaii, M.J. Yazdanpanah. "A new method for control of finite-energy systems with H_∞ controllers", (in Farsi), 9th Iranian conf. On Electrical Engineering proceedings, (2001).

[11] T. Tigrek, S. Dasgupta, T.F. Smith. "Nonlinear optimal control of HVAC systems", Proceedings Of IFAC World Congress, (2002).

[12] C.P. Underwood. "HVAC control systems: modeling, analysis and design", E & FN SPON pub., (1999).

[13] C.P. Underwood. "Robust control of HVAC plant I: modeling ", *Proc. CIBSE*, **Volume** 21, No. 1, (2000).

[14] C.P. Underwood. "Robust control of HVAC plant II: controller design ", *Proc. CIBSE*, **Volume** 21, No. 1, (2000).

[15] Q.G. Wang, C.C. Hang, Y. Zhang, Q. Bi. "Multivariable controller auto-tuning with its application in HVAC systems", Proceedings Of ACC, (1999).

[16] M.J. Yazdanpanah. "Toward minimization of actuator repositioning", Internal Report, Dept. of ECE, Concordia University, (1997).

[17] M.J. Yazdanpanah, M.R. Omidi. "Control signal smoothing by optimal controllers", (in Farsi), 8th Iranian Conf. On Electrical Engineering, (2000).

[18] M.J. Yazdanpanah, M. Tavanaii. "Minimization of control signal oscillations in time-delayed systems by H_∞ methods", (in Farsi), 8th Iranian conf. On Electrical Engineering, (2000).

[19] M.J. Yazdanpanah, M. Zaheeruddin and R.V. Patel, "Feasibility study of adaptive control algorithms", Technical Report, Dept. of ECE, Concordia university, (1997).

[20] M.J. Yazdanpanah, E. Semsar, C. Lucas, "Minimization of Actuator Repositioning in Delayed Processes Using Flexible Neural Networks", Conference on control application Proc., **volume** 1, pp. 331-335, (2003)

PID1	Kp	Ki	Kd
Z.N	-2e-4	-.1	0
C.C	-2.3e-4	-.09	0

Table 2: PID gain tuning for first output

PID2	Kp	Ki	Kd
Z.N	-.015	-22.5	-2e-5
C.C	-.018	-21.4	-2e-5

Table 3: PID gain tuning for second output

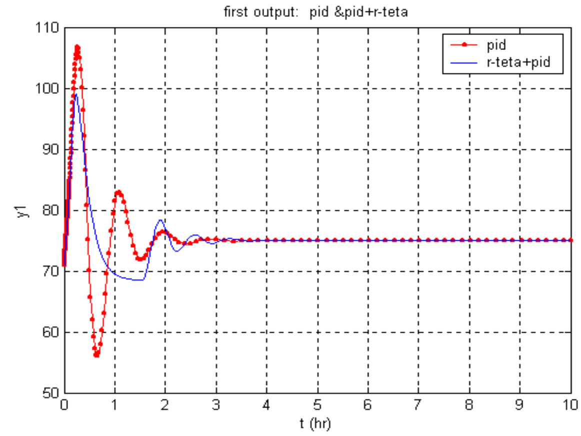

Figure 3: First output using PID and PID+ H-limitter

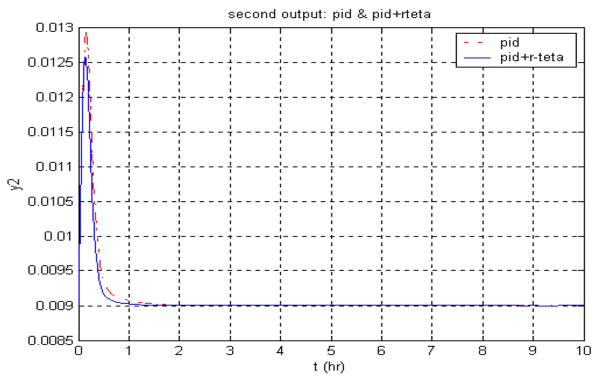

Figure 4: 2^{nd} output using PID and PID+ H-limitter

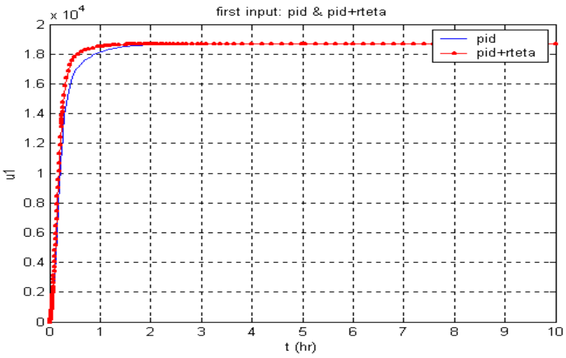

Figure 5: First input using PID and PID+ H-limitter

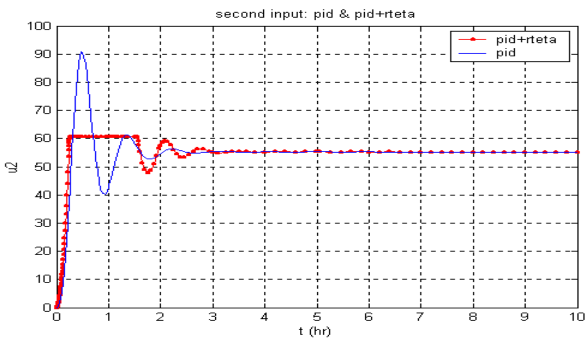

Figure 6: Second input using PID and PID+ H-limitter for Quintic trajectory

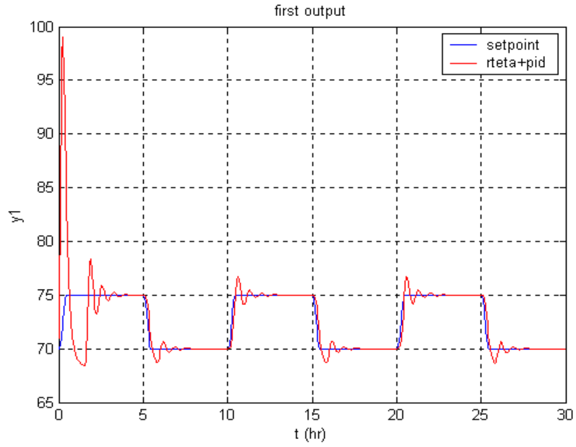

Figure 7: 1^{st} output using PID+ H-limitter: a square waveform

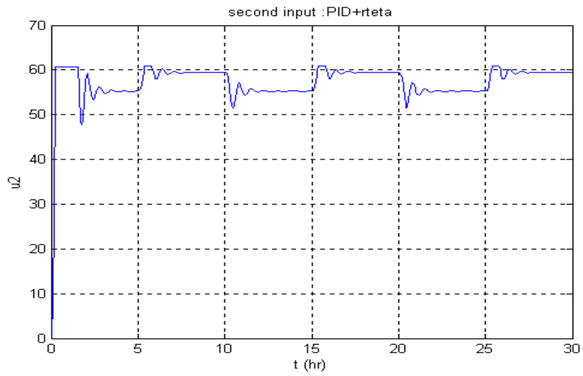

Figure 8: 2^{nd} input using PID+ H-limitter: a square waveform

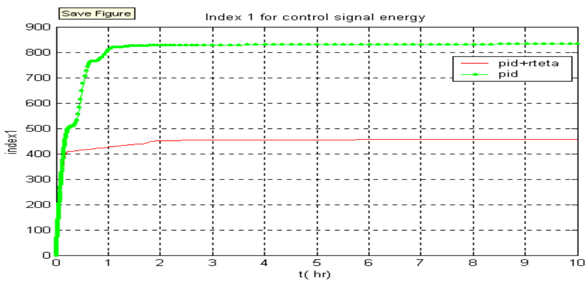

Figure 9: First index using PID and PID+ H-limitter for control signal energy

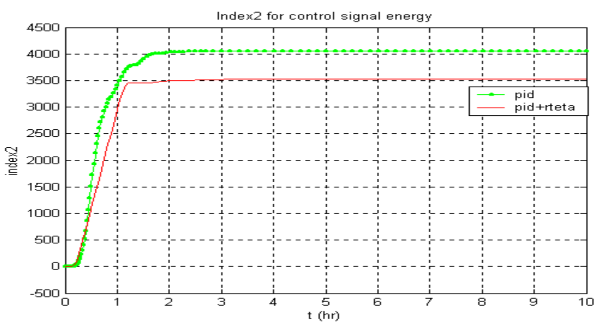

Figure 10: Second index using PID and PID+ H-limitter for control signal energy