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Online Tuning of Adaptive-Optimal PID Controllers via Artificial Neural Networks

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ABSTRACT: *This research presents a methodology for online tuning of artificial neural network parameters that are in the context model predictive control (MPC). This MPC system design is composed of anadaptive-optimal PID controller. The Artificial Neural Network RBF represents the algebraic structure of the PID, in order to meet not only the design requirements, but also to present properties of adaptability and optimality at each instant of sampling. Also in this article, the proposal of an adaptive PID control structure based on the predictive neural network model for controller tuning is presented. The artificial neural networks guarantee a satisfactory incorporation of dynamics of the process to be controlled, being a one-step neural network to predict the output of the process. The proposal is evaluated in photovoltaic panel, the adaptive-optimal PID controller results are compared to the classic PID model.*

Keywords: *tuning, online, Neural Networks, controller, PID, Radial Basis Function and Adaptive.*

I. INTRODUCTION

Online applications have bottlenecks that require an investigation of their implementation so as not to compromise real-time projects.For example, optimization methods require large computational efforts, which often tend to fail with the complexity of the dynamic system.The motivation for employing bio-inspired stochastic optimization algorithms as computationally efficient alternatives to the deterministic approach [1].
Frequently, optimal control theory provides the support to solve automation problems in electrical, mechanical, and industrial processes. Often, the physical nature of these processes introduces time delays. In engineering systems delays are often present due to measurement, transmission and transport lags, computational delays, or unmanaged inertia of the system components [2]. In control systems, it is known that time delays can undermine system performance and even cause [3].

At the beginning of the millennium, the PID controller remains a key component in the control of industrial processes. During the last century many different combinations of structures have been proposed to overcome the limitations of PID controllers.Due to its simplicity and use it has proven to be a powerful solution for the control of a large number of industrial processes [4]. This control model is quite popular and used in the industrial field due to the ease of design and implementation at low cost [5]. However, the optimal tuning for controller gain is still challenging and motivating. In a number of books and articles, such as PSO evolution algorithms [6], DE [7], GA [8], among others have been used to tune PID controllers.

The adaptive control approaches in [9], [10], [11] and the references [12][13]contribute to the application framework. The optimal control approaches contribute to the degree of freedom of the designer to meet and systematically insert energy consumption constraints.

The demand for high performance control systems is a pressing need of the contemporary world as can be seen in references that show applications in industrial, power and aeronautical systems.In this way, the demand for new architectures and topologies that surpass or add value to the closed-loop control system design in the classical sense is perceived. These new systems must satisfy the randomness of the operation (human errors), cost reduction in the production of added value of the final product and process variations.The development of intelligent control systems with the properties of adaptability, prediction and learning associated to computational intelligence and prediction approaches within a control horizon with the classic parametric estimation methodologies in order to obtain the tuning of gains of transfer functions of the Adaptive and optimal control meshes. The union of these approaches has shown to be an attractive alternative for real-time tuning of the parameters of estimators and controllers in real-world systems.

The present article presents the procedure for implementing an adaptive - optimal PID controller in a position control of a solar panel. Then compared to a classical PID tuning method.The implementation is associated to the online algorithm that is developed for parameter adjustments in control systems with adaptive-optimal PID architecture. In terms of hardware, indoor performance is used for performance tuning method of parameters. The reduced model of real-world plant such as: position control of a Solar Panel.The article is organized in sections that present the proposed methodology and its development, the adaptive and optimal algorithms, the embedded system and the evaluation test.

II. PROBLEM CHARACTERIZATION AND SOLUTION

In this section we present the problem-solving characterization that consists of the description of the problem of the online tuning of PID controllers and their formulation. The following is the presentation of the mathematical formulation of the solution method that develops algorithms online via computational intelligence for online tuning of the PID-optimal controllers.

A description of the online tuning method ofPID controllers. Generally, it is impossible to obtain a physically appropriate model of dynamic industrial automation and electrical power systems due to the complexity of the underlying processes or the lack of knowledge of critical parameters (such as mass transfer coefficients, Heat, or viscosities dependent on temperature and pressure) of the models.

One way to overcome these problems of process modeling, it is to use neural networks as nonlinear black box models of the dynamic process behavior [14]. As described in the article we demonstrate, the measurements of input and output variables of the process operated with the linear controller can provide very good training data for the predictive neural network.

II.1. MATHEMATICAL FORMULATION OF THE PROBLEM

The mobile target problem consists of the steps of detecting the presence of the crawled object and the second step consists of positioning devices to extract information that characterizes the target in question. The characterization of the process allows the extraction of parameters, such as time constants, gains and stability, that allow to establish restrictions or specifications to meet the control requirements. Mathematical modeling of the dynamic process, input and output, in discrete form:

$$\mathrm{y(k)} = -\mathrm{a}_1 y(k-1) - a_n y(k-n) + b_0 u(k) + b_1 u(k-1) + b_m u(k-m) \quad (1)$$

Modeling the PID Controller in equations the difference in the form of Euler,

$$\mathrm{u(k)} = \mathrm{K}\left[e(k) + \frac{T_0}{T_i}\sum_{i=0}^{k} e(i-1) + \frac{T_d}{T_0}\Delta e(k)\right] \quad (2)$$

For the definition of $\Delta e(k) = e(k) - e(k-1)$.

Structure of the Prediction RBF network, Fig. (1), given by 6-5-1.

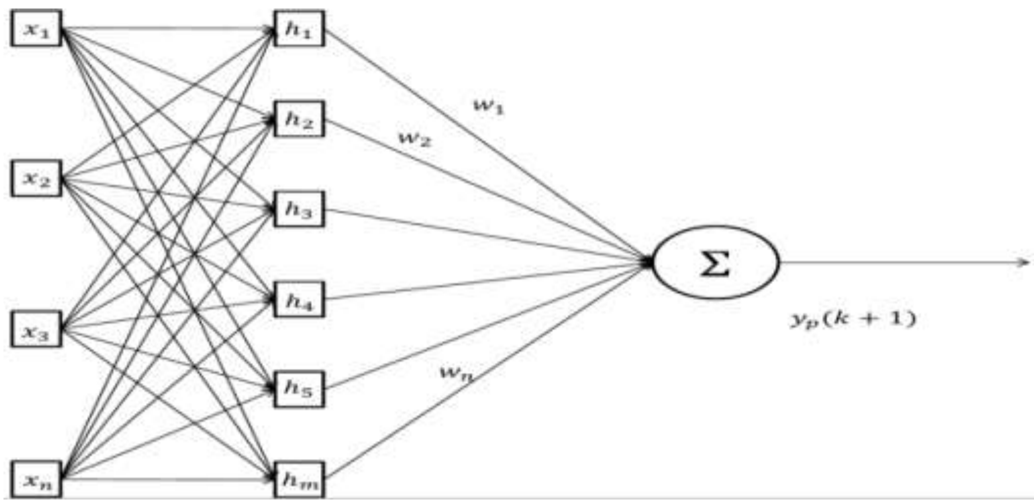

Figure 1: Structure of Neural RBF Predictive

The input of the network is composed of six sensory units, the current output of the system and two outputs being delayed, the other three being formed by the current input of the system with the two delayed ones. The input represented by vector $\mathbf{x}_p = [x_1, x_2, x_3, x_4, x_5, x_6]$ and the output of the prediction network is

$y_p(k+1)$. The input and output of the RBF Predictive Neural Controller. Input of the control RBF network is defined by the vector $\mathbf{x}_c = [x_1, x_2, x_3]$ and the output of the controller is $u(k)$.

The RBF Artificial Neural Network is used for adaptive neural PID controller architecture. The RNA is designed with three layers (3-5-1) in consideration of the real-time requirement of the control system. The structure of the neural PID controller is developed by the direct method, in order to abort the output of the controller through the inputs of the neural network RBF Fig. (2).

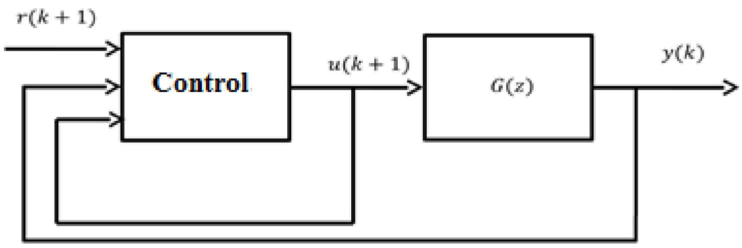

Figure 1:Proposed controller scheme.

The structure of the neural network can be written in function of J that is given by

$$J = \frac{1}{2}\left[r_d(k+1) - y_p(k+1)\right]^2 \quad (3)$$

The steepest descent method is used to adjust the network weights to reach the goal of J.In this way $e(k+1) = \left[r_d(k+1) - y_p(k+1)\right]$.The criterion of Eq. (3), the output of the controller $u(k)$ already defined the input vector of the neural network RBF, has the input of the hidden layer $h_c = c_c x_c$. The x_c represents the input and c_c represents the center of the RBF. And for the input of the controller's neural network RBF is defined as: $x_1 = e(k), x_2 = T\sum_{i=0}^{k} e(k)$ and $x_3 = \frac{\Delta e(k)}{T}$.

II.1. PID-Adaptive-Optimum Control System

The structure of the neural PID controller is developed by the direct method, in order to abort the output of the controller through the inputs of the neural network RBF.The neural network consists of three sensory units in the inputs, five neurons in the hidden layer and one neuron in the output layer, (3-5-1). The output of each neuron from the hidden layer is $O_c = f_{RBF}(I_h)$, The input of neuron I_h and O_h of the hidden layer,

$$I_O = W f_{RBF}(I_h) \quad (4)$$

The output of the RBF network provides the control action $u(k)$.

$$u(k) = f_O(I_O) \quad (5)$$

The function of the network output layer f_o is linear. The update of the RBF neural network parameters of control is used the descending gradient method,which is used Eq. (3),

$$E(k) = \frac{1}{2}\left(r(k+1) - y_p(k+1)\right)^2 \quad (6)$$

With the following conditions met,

$$\Delta w_j(k) = -\eta \frac{\partial E}{\partial w_j} = -\eta e(k)(y(k) - y(k))\frac{\partial y(k)}{\partial u(k)} h_j \quad (7)$$

$$\Delta b_j(k) = -\eta \frac{\partial E}{\partial b_j} = \eta e(k)\frac{\partial y(k)}{\partial u(k)}\frac{\partial u(k)}{\partial b_j} \quad (8)$$

$$\Delta c_j(k) = -\eta \frac{\partial E}{\partial b_j} = \eta e(k)\frac{\partial y(k)}{\partial u(k)}\frac{\partial u(k)}{\partial c_j} \quad (9)$$

To update the weights w_j, b and c of the control network.

$$w_j(k) = w_j(k-1) + \Delta w_j(k) + \alpha \Delta w_j(k) \quad (10)$$

$$b_j(k) = b_j(k-1) + \eta\Delta b_j(k) + \alpha(b_j(k-1) - b_j(k-2)) \tag{11}$$

$$c_{ij}(k) = c_{ij}(k-1) + \eta\Delta c_{ij}(k) + \alpha(c_{ij}(k-1) - c_{ij}(k-2)) \tag{12}$$

Where η and α are the learning rate and moment factor, respectively. For the next updates of the b and c parameters.Where $\frac{\partial y(k)}{\partial u(k)}$ is the Jacobian value that expresses the output and input sensitivity of the system. This value can be obtained by the signal of $\frac{\partial y(k)}{\partial u(k)}$.

III. TRACKER DESIGN AND IMPLEMENTATION

Within a context of possessing properties of adaptability and optimality. The proposed control system is based on adaptive-optimum PID controllers.

III.1. Tracking Control System

The block diagram of Fig.(2) represents control system for photosensitive tracking. The block diagram represents the process, a gearmotor and sensors that are modeled by means of ordinary differential equations for the purpose of equipment specification and development of the control algorithms.The purpose of the control is to track Luminous Intensity (IL) variation, in this case not by the apparent rotation of the sun, but to track IL caused by a circular artificial light system at a rate of $1m/s$. The dynamic system receives the IL by the sensor set formed by the two LDRs and sends it to the control unit. The actual system is shown in Fig. (3).

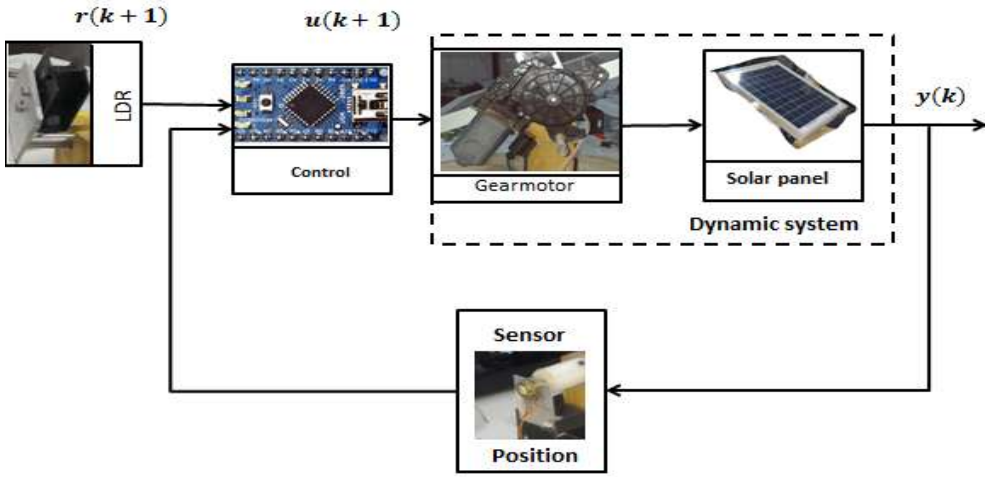

Figure 2:Block diagram of the photosensitive tracking system

In the summation a second-order mathematical model is used, which is the controlled model. The RBF neural PID controller with a 3-5-1 structure and for the predictive neural network is used a 6-5-1 structure network.

Figure 3:Photosensitive tracking system

III.2. Mathematical Modeling of the Tracking Control System

The transfer function $G(s)$ of the actuator (motor) and the process (panel). The moment of inertia $(J_m = 3,2\times10^{-6}\,kgm^2)$ and the coefficient of friction $(b_m = 5,5\times10^{-6})$ of the motor are negligible with respect to the moment of inertia $(J_p = 100kgm^2)$ and the coefficient of friction $(b_m = 1)$ of the panel. Thus, the moment of inertia and the coefficient of friction of the motor are replaced by that of the panel in the modeling of the plant.

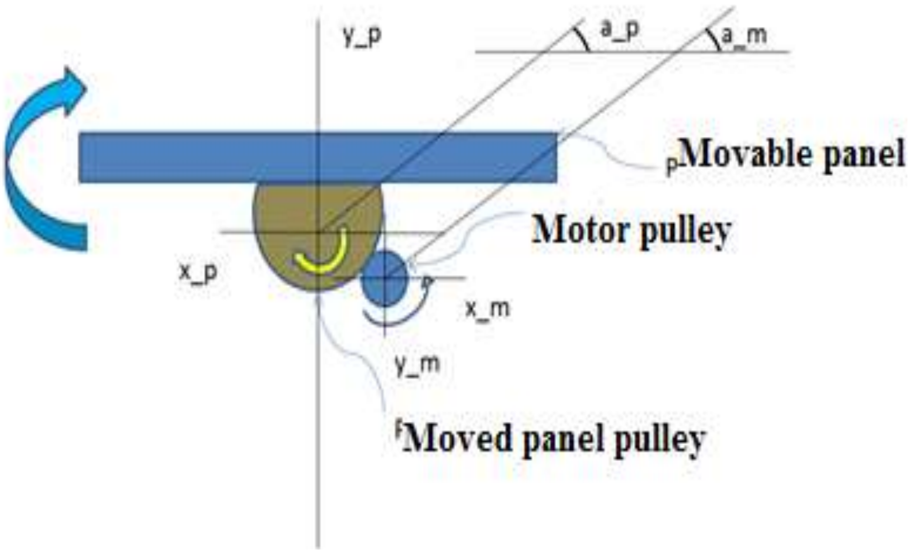

Figure 4:Mathematical modeling of the solar panel

Thus, the system transfer function, taking into account the relation between the angle of the axis a_m of the motor and the panel angle (a_p) according to Fig.(4), is:

$$\frac{\Theta(s)}{V_c(s)} = \frac{10\pi K_M}{\pi[(RJ_p s^2 + Rb_p s) + K_b K_M s] + 10K_M} \qquad (13)$$

The motor parameters $R_a = 4\Omega$, $L = 2.75*10^{-6}$, $b_m = 3.5077*10^{-6}$ and $K_m = 0.0274$ were obtained by means of the datasheet supplied by the manufacturer. However, for many DC motors, in relation to their modeling for control purposes, the effect of armature inductance is disregarded. For this situation the system is stable, it has no poles on the right side of plane s. Applying a step input in the system to verify its behavior.

III.3. Elements of the Control System

Following a conventional taxonomy, the elements of the control system of Fig. 2 are classified as process, load, sensors, actuators and control unit.

III.3.1 Process and Load

For control purposes, the tracking process of the moving body (Sol) is composed of loads distributed in fixed and varied loads. The fixed load is the sum of the frictional forces of the sliding bearings. The varied load is composed by the moment of inertia and natural and normal reactions.

III.3.2 Sensors

The process consists of two sensors: sensor for tracking, LDR, a passive electronic component of variable resistor type, whose resistance varies according to the intensity of the light that falls on it. Responsible for the location of the mobile body (Sol) and has the important role of reference of the control system. Locating sensor, Linear Potentiometer, with curve of constant resistance variation (linear) in relation to the angle of rotation of the axis. The position of the movable table is verified by the potentiometer and sent to the control system.

III.3.3 Actuators

The 12V / 75RPM gearmotor, Celeron gear, sliding bearing at gear unit output, insulation class of 180 °C, model CEP 9 and manufacturer BOSCH. It is coupling on the axis of the turntable and has the function of moving the movable set of the turntable, composed of axis, solar panel and sensors.

III.3.4 Control Unit

It consists of an 8-bit Atmel ATmega328 microcontroller with modified Harvard architecture. It belongs to the AVR family of Atmel. It has a basic architecture and set of instructions, particularly the tinyAVR (ATtiny microcontrollers), megavR (the ATmega) and XMEGA (the Atxmega).

IV. DISCUSSION OF THE RESULTS

For the analysis of the classic PID controller we have the values of K_p, K_i, and K_d that satisfy the requirements of the project are respectively 277.1884, 3.8166 and 1181.7030. Using these values and analyzing their behavior. The tuning of the PID controller using the method proposed by Ziegler-Nichols. For the behavior of the system the transient response of the system, one has the rise time, 1.75 s, accommodation time, 12.4344 s and Overshoot 14.6050.

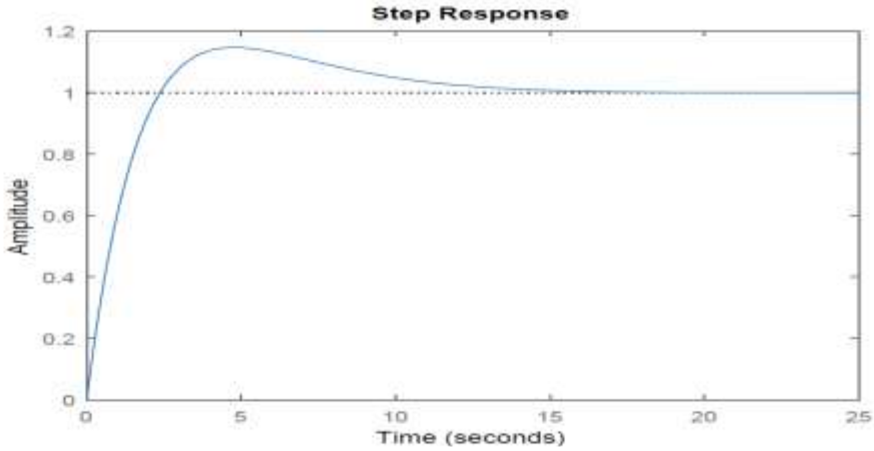

Figure 5:Step response

The prediction of dynamic system output is based on an online training RBF network. The input of the neural network is composed of six sensory units, the current output of the system and two outputs delayed, the other three is formed by the current input of the system with the two delayed ones. From the predictive neural network Fig. (1).For the prediction of the output of the dynamic system at the instant of $(k+1)$ is acquired, using the function approximation tool an RBF neural network with structure 6-5-1. Where the red line represents the behavior of the object and the dashed black line represents the prediction in a step ahead of the process.

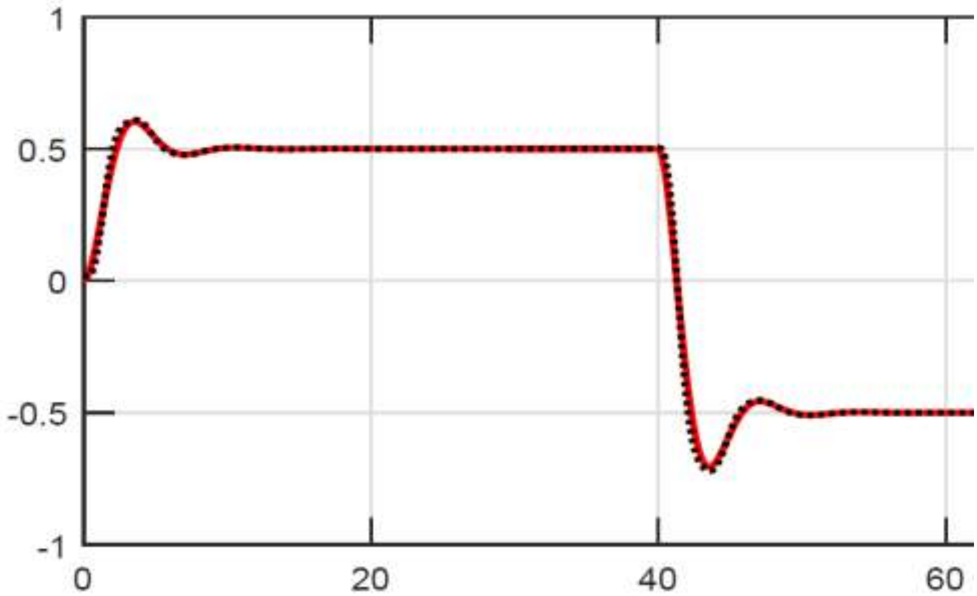

Figure 5:Prediction of system behavior

The Adaptive PID-RBF controller has a 3-5-1 structure, the J function is described in (3). The input of the network is a linear combination according to the error, described in detail in Section II. The input vector of the network $\mathbf{x}_c$ and the output of the neural network being the signal of the controller.

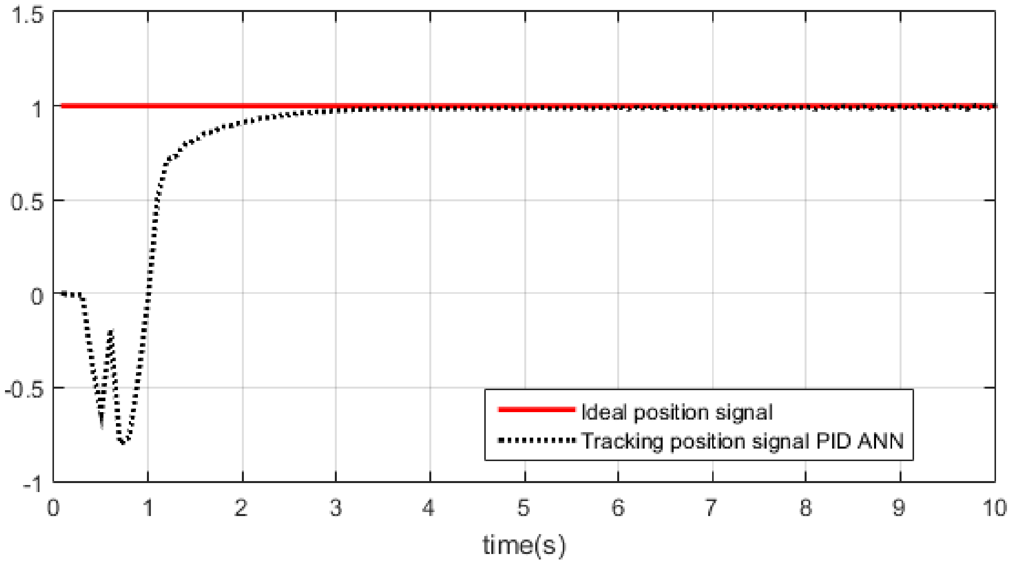

Figure 6:Response to the system step with the PID controller with online tuning

The adjusted RBF neural network parameters are only the momentum photometer (0.12) and the learning coefficient (0.35). The other factors (RBF centers and length) are adjusted online and adaptively.

V. CONCLUSION

This article presented a new design methodology to attend the new technological demands that require the action of systems of high operational performance. The proposed method has characteristics of adaptability that is represented by the adaptive control and the optimality that is served by the optimal control approaches.

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