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Neural Estimator Automatic Fluorescent Daylight Control System

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Abstract

The daylight control system represents an electric light system used in office or design laboratory applications. The system tries to maintains constant the illuminance level on the working plane even the daylight contribution is variable. From other point of view the daylight control system is the lighting system that compensates the daylight variation in a room (office, design laboratory). The importance of this type of lighting system is that it satisfies the following requirements: user visual comfort and electrical energy savings. Considering these requirements the lighting system has to be implemented such an automatic control system with negative feedback. The behavior of the automatic lighting system will depend mainly on the controller behavior. In the present paper, a feed-forward artificial neural network (FANN) was chosen to control the lighting process using the Control by Estimation Iterative Algorithm. Due to the control strategy for a stable behavior of the automatic lighting control system without or with acceptable overshoot (regarding the control system step response) the learning rate of the FANN needs to have very small values and in a short range. To remove this shortcoming in present paper is proposed a modified learning error which allows the learning rate to have a wider range of values for which the automatic lighting control system has a good behavior. Also, is proposed a new way that the user can modify the speed reaction of the automatic control system regarding the daylight changes.

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Keywords: artificial neural network; estimation; automatic daylight control system; fluorescent lamp.

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1. Introduction

Since Rosenblatt proposed the Perceptron model, the first artificial neural network (ANN) which can learn from example, the ANNs reach the attention of the researcher and engineers. Nowadays, due to their learning and approximation capabilities, the ANNs became a comfortable choice regarding the process identification and control. In [10] the authors used as the on-line system identifier a NARX model based on a kind of feedforward artificial neural network (based on wavelet analysis) known as recurrent wavelet neural network. The identification results are used in a predictive ship course control simulation to shows the effectiveness of the proposed identification method and control strategy. The authors from [6] use the neural network predictive control strategy to control a continuous stirred tank reactor. For process identification it was used two types of a FANN (Multi-Layer Perceptron – MLP, Radial Basis Function – RBF) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). Yang and Wu propose in [9] an adaptive control scheme (based on artificial neural network nonlinear identification) for an induction motor and show the better adaptability and stronger stability of this control system over the PID control system. In [7] the authors simulate via the Matlab Simulink models, the control of an Unmanned Aerial Vehicle using the model reference control strategy based on two ANNs: first ANN is used for process identification and the second is used as controller. The plant model is identified first, and then the controller is trained so that the plant output follows the reference model output. Tran and Tan use in [8] a FANN to model the nonlinear relation between dimming levels of LED luminaires and illuminance tables in case of a networked LED-lighting system. The obtained neural model is used, in simulation, in a sensorless illumination control. The experimental results show the energy saving functionality of the proposed approach.

2. The automatic lighting control system

The used experimental stand is the same one used in [3] and is presented in Fig. 1a and is composed by the following components: the computer (1), the technological installation (2), the lighting sensor (3), data acquisition board (4) and the working plane (5). The computer represents the calculation machine on which will run the code machine source of the used artificial neural network. The technological installation is composed by the lighting process (accomplished with two 36W warm white fluorescent lamps) and the execution element (accomplished with the following modules produced by Tridonic: a DSIA/D converter and a digital ballast PCA 2/36 EXCEL). The lighting sensor represents a multifunctional LRI 8133/10 sensor produced by Phillips. The data acquisition board has two 1 byte conversion channels: one A/D channel used for the acquiring of the data from lighting sensor and the other channel a D/A channel used to send the command from computer to the execution element. The working plane represents the surface of the desk on which the user of the automatic lighting control system executes different office tasks.

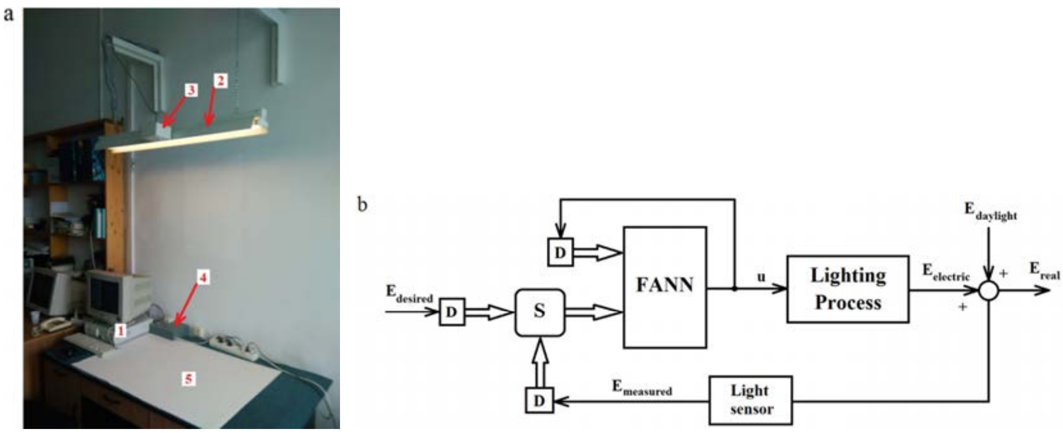

Fig. 1. The ALCS: (a) The experimental stand; (b) block diagram

In Fig. 1b is presented the block diagram of the used automatic control system where was denoted by: $E_{electric}$ – the electric illuminace which represents the illuminance level on working plane due to the electric light (the fluorescent lamps); $E_{daylight}$ – the daylight illuminance, represents the illuminance level on working plane due to the amount of daylight through the room window; E_{real} – the real illuminace, represent the illuminance level on working plane due to the summation of $E_{electric}$ and $E_{daylight}$; $E_{measured}$ – the measured illuminance, represents the real illuminance level on working plane measured by the A/D channel of the acquisition board; $E_{desired}$ – the desired illuminance, represents the desired illuminance on working plane; u – the command applied to the lighting process (through the acquisition board D/A channel and the execution element presented above); D block represent a delay net used to create at its output a vector of past values of the signal which is applied to the block input; S block represent a selector use to select which vector of illuminance past values is applied to the input of the regulator.

To achieve the process control task the Control by Estimation Iterative Algorithm (CEIA) was used. The CEIA was proposed by Grif in [5]. In case of this control algorithm the regulator, implemented by an feedforward artificial neural network (FANN), is used as an estimator of the current command based on the past values of the command and illuminance. Shortly described, the CEIA has two main tasks: first task is the estimation process which is performed by the FANN by computing the current desired command ($u(kT)$, T is the sample time, k = 0,1,…) using the past values of command ($u((k\text{-}1)T)$ and $u((k\text{-}2)T)$) and the past values of desired illuminance ($E_{desired}((k\text{-}1)T)$, $E_{desired}((k\text{-}2)T)$ and $E_{desired}((k\text{-}3)T)$); the second task represent the FANN training process performed considering the learning error given by

$$\varepsilon(kT) = u(kT) - \tilde{u}(kT)\,, \tag{1}$$

where the $\tilde{u}(kT)$ represent the command calculated by the FANN considering at its inputs the past values of command ($u((k\text{-}1)T)$ and $u((k\text{-}2)T)$) and the past values of the measured illuminance on working plane ($E_{measured}((k\text{-}1)T)$, $E_{measured}((k\text{-}2)T)$ and $E_{measured}((k\text{-}3)T)$). The classical generalised Delta [1, 2, 3] rule was used for training the FANN.

The regulator is implemented by a FANN with five inputs and one output. The first two inputs are used for the past values of command and the next three inputs are used for the past values of the illuminance. The FANN consists of three layers: the input layer, the hidden layer and the output layer. The hidden layer has six neurons like in [InterIng2013] with hyperbolic tangent type activation function. The neuron from the output layer has the linear with saturation type activation function.

3. Experimental results

In the case of the used process, a lighting process, the human eye perception is the main factor for the settlement of the performances which have to be satisfied by the ALCS. The assessed performances are: the overshoot of the ALCS response should be less or equal to 7% [4] and the steady state error should has values less as $\pm 0.07 \cdot E_{desired}$. The desired illuminance level on working plane is $E_{desired}$ = 100 lx_{d8bv}. The meaning of abbreviation d8bv is "digital 8 bits value". The value 100 lx_{d8bv} represents the equivalent value obtained by conversion with the acquisition board A/D channel of the 500 lx illuminance level measured on the working plane by an analog illuminance measuring device. The sampling time is set to 0.055 seconds. The experiments were achieved under the night condition. The FANN is implemented in C language and run on the computer from Fig. 1a.

In Fig. 2 are depicted the step response family when the learning rate (γ) is variable. The increasing of the learning rate will reduce the transient period but will increase the overshoot. Analyzing Fig. 2 the ALCS step response is without overshoot or the overshoot is less than 7% for a learning rate less or equal than 0.035.

To increase the reaction speed of the ALCS and to extend the values intervals for learning rate the authors propose the following learning error:

$$\varepsilon(kT) = (u(kT) - \tilde{u}(kT)) + G_{\Delta E}(E_{desired}(kT) - E_{measured}(kT))\,, \tag{2}$$

where $G_{\Delta E}$ represents the gain of control error. The results presented in Fig.2 was achieved considering the learning error calculated with $G_{\Delta E} = 1$. All values of the variables from (2) and the FANN input/output values are mapped to the real domain [-1.0, 1.0].

Considering the variable $G_{\Delta E}$, the authors performed a study related to the influences of this parameter in terms of the ALCS step response. The study was achieved for the learning rate values for which the ALCS step response overshoot is over 7%. For each value of the learning rate, was acquired the step response family corresponding to the increasing the $G_{\Delta E}$ parameter from 0.05 to 0.95 with a step of 0.05. After the analyzing of each step response family was selected the values domain for $G_{\Delta E}$ (see the second column of Table 1) for which the ALCS step responses have an overshoot less or equal to 7% and the maximum transient period is less than 25 seconds. In the third column of the Table 1, for each learning rate is presented the minimum value of the transient period corresponding to the maximum value of $G_{\Delta E}$. The minimum transient period is less 2 seconds for $\gamma \in [0.04, 0.3]$ and over 2 seconds for the rest. The higher the learning rate the more the $G_{\Delta E}$ domain narrows.

Table 1. The $G_{\Delta E}$ domains and the minimum transient period corresponding to the FANN learning rates.

Learning rate (γ)	$G_{\Delta E}$	Minimum transient period [s]
0.04	[0.05, 0.85]	1.65
0.05	[0.05, 0.65]	1.65
0.06	[0.05, 0.55]	1.705
0.07	[0.05, 0.5]	1.595
0.08	[0.05, 0.45]	1. 595
0.09	[0.05, 0.4]	1. 595
0.1	[0.1, 0.35]	1. 595
0.2	[0.15, 0.35]	1.485
0.3	[0.2, 0.35]	1.76
0.4	[0.3, 0.39]	2.365
0.5	[0.3, 0.38]	2.75
0.6	[0.3, 0.38]	3.135

As example, in the Fig. 3, is presented the ALCS step response family according to the $G_{\Delta E}$ variation in the interval [0.05, 0.95], for the learning rate γ=0.04. The increase of the $G_{\Delta E}$ will decrease the transient period but will increase the overshoot. Based on this step response family, considering γ=0.04, the authors chose $G_{\Delta E} \in [0.05, 0.85]$. For this interval the overshoot of ALCS step response is less than 7%. The minimum transient period takes 1.65 seconds and is achieved for $G_{\Delta E} = 0.85$ (Fig. 3b).

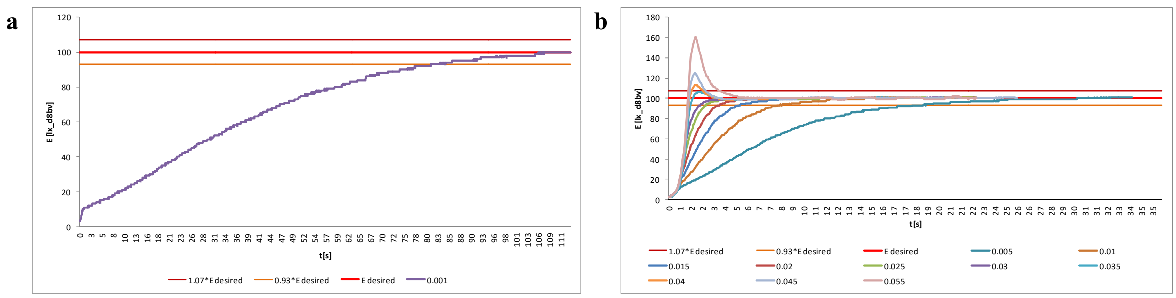

Fig. 2. The ALCS step response family: (a) γ= 0.001; (b) γ= 0.005÷0.055

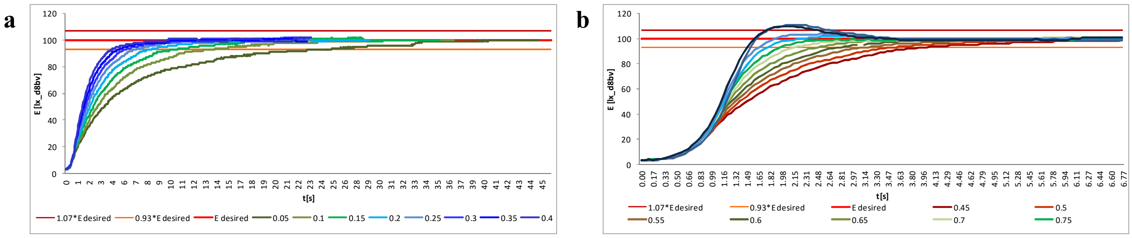

Fig. 3. The ALCS step responses family (γ= 0.04): (a) $G_{\Delta E}$= 0.05÷0.4; (b) $G_{\Delta E}$= 0.45÷0.95

4. Conclusion

The control strategy applied to a real fluorescent lighting process presented in this paper represents the continuations of the studies started by the first author in [5] where a halogen lighting process was used. The experimental results from the present paper represent another proof for the effectiveness of the CEIA algorithm. Also the authors introduced the use of the gain of control error which establish how much from the control error is used in the FANN learning signal. The use of this gain helps to extend the domain of the learning rate (almost 20 times wider) such that the overshoot of the ALCS step response is smaller or equal than 7%. Another benefit of the introducing of the gain of control error parameter is the use of this parameter as an adjustment "button" for ALCS speed reaction which allows the users (the office occupants) to set their own reaction of the automatic daylight system to the daylight changes.

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