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Offline Auto-Tuning of a PID Controller Using Extended Classifier System (XCS) Algorithm

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Abstract — **Proportional + Integral + Derivative (PID) controllers are widely used in engineering applications such that more than half of the industrial controllers are PID controllers. There are many methods for tuning the PID parameters in the literature. In this paper an intelligent technique based on eXtended Classifier System (XCS) is presented to tune the PID controller parameters. The PID controller with the gains obtained by the proposed method can robustly control nonlinear multiple-input–multiple-output (MIMO) plants in any form, such as robot dynamics and so on. The performance of this method is evaluated with Integral Squared Error (ISE) criteria which is one of the most popular optimizing methods for the PID controller parameters. Both methods are used to control the ball position in a magnetic levitation (MagLev) system and the performance of controllers are compared. Matlab Simulink has been used to test, analyze and compare the performance of the two optimization methods in simulations.**

Keywords — **Artificial Intelligence; Extended classifier system; Magnetic levitation; PID controller tuning**

I. INTRODUCTION

Proportional + integral + derivative (PID) controllers are extensively used in the industry. In 2001, it was estimated that more than 90% of all control loops involved PID controllers [1]. Today this proportion decreased to more than 50% but still PID controller is the most popular controller in the industry. The simplicity, transparency, reliability and high efficiency are the most important reasons for this widespread popularity [2].In the absence of underlying process knowledge, a PID controller has traditionally been considered to be the best controller [3]. The drawbacks of this control technique, mostly for nonlinear systems, include the difficulty in selecting appropriate controller gains, a procedure which usually referred to as tuning. The difficulty usually lies in the fact that if the controller gains are set too small, the control objective may never be reached, whereas the selection of excessively large controller gains may result in system instability [4]. When a mathematical model of a system is available, the parameters of the controller can be basically determined. However, when a mathematical model is not available the parameters must be determined experimentally. Controller tuning is the process of determining the PID parameters which generate the desired output. Controller tuning allows for optimization of a process and minimizes the error between the process output and its desired value (i.e. the set point).

One of the most well-known criteria for optimizing the PID parameters is the integral of the squared error (ISE) criteria since the relevant integral can easily be evaluated in the frequency domain. This criteria is used when the

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mathematical model of the system is available [5].

There are several methods in the literature for tuning the PID parameters, which include some modern techniques. Ang et al presented a modern overview of functionalities and tuning methods, software packages and commercial hardware modules [6]. Pyung et al presented asystematic method to select gains of a discrete PID controller [7]. Coelho et al used a chaotic optimization approach based on Lozi map for tuning the PID parameters [8]. He et al presented a new optimal PI/PID controller tuning algorithms via LQR approach [9].Awouda et al demonstrated an efficient method of tuning the PID controller parameters using the optimization rule for ITAE performance criteria [10].Bagis presented an efficient and fast tuning method based on a modified generic algorithm structure to find the optimal parameters of the PID controller [11]. And Stephen et al formulate multi-input multi-output proportional integral derivative controller design as an optimization problem [12].

There are many methods to control ball position in the magnetic levitation that presented in the literature. These controllers include classical PID, feedback linearization, state feedback etc. In this paper, first the ISE criteria for PID tuning is applied to magnetic levitation (MagLev) system, referred to as ISE-PID system. This controller is designed within MATLAB. Next a new PIDtuning method based on artificial intelligence is presented. XCS (eXtended Classifier System) approach is used to adjust the parameters.The position of the ball in the magnetic levitation system is controlled by XCS tuned PIDgains, referred to as XCS-PID system. This method is implemented in the system using MATLAB programming and Simulink. Finallytheperformances of ISE-PID and XCS-PID systemsare compared.

The paper is outlined as follows: In Section 2 a general description of magnetic levitation system and its mathematical model is described. Details of XCS algorithm are presented in Section 3. The simulations to achieve the objectives of the paper are presented in Section 4 and finally concluding remarks are presented in Section 5.

II. MAGNETIC LEVITATION AND MATHEMATHICAL MODEL

Magnetic levitation (MagLev) is a system using electromagnetic forces to suspend a ferromagnetic object in the air without any contact. The electromagnetic forces overcome the effect of gravity and provide stable equilibrium of the object.

In this section we describe the physical system briefly, which is the foundation of this research, followed by corresponding mathematical model of MagLev. By assuming linear characteristics of used materials, the magnetization density solely on the magnetic field density [13]. The beneath function can approximate magnetic flux

$$\lambda(t) \triangleq \lambda\big(i(t), x(t)\big) = L\big(x(t)\big).\, i(t) \qquad (1)$$

where *i(t)* indicates the current through the solenoid, and *x(t)* denotes the displacement of levitation object compared to solenoid bottom. *L(x)* indicates the total inductance and by assumption of being a function of *x(t)* has the following form [14]

$$L(x) = L_1 + \frac{L_0}{1 + (\frac{x(t)}{a})} \qquad (2)$$

where $L_0 = L(0) - L(\infty)$, $L_1 = L(\infty)$ and a is a constant coefficient.

According to the electromagnetic theory [12], the magnetic co-energy,W is described by:

$$W(t) = \int_0^{i(t)} \lambda\big(\bar{\imath}, x(t)\big) d\bar{\imath} \qquad (3)$$

By inserting (1) and (2) into (3), we conclude:

$$W(t) = \frac{1}{2}\left(L_1 + \frac{L_0}{1 + \left(\frac{x(t)}{a}\right)} \right) i^2(t) \qquad (4)$$

The magnetic force, *f(t)* is obtained from the magnetic co-energy by

$$f(t) = \frac{dW(t)}{dx_a} \qquad (5)$$

By neglecting the air friction, the dynamics of the levitation object is determined by Newton's second law as

$$m\frac{dx^2(t)}{dt^2} = mg + f(t) = mg - \frac{1}{2}\frac{L_0\, i^2(t)}{a\left(1+\frac{x(t)}{a}\right)^2} \qquad (6)$$

where m and g denotes the mass of the levitation object and the gravity acceleration respectively.

Denote the coil resistance as R and the input voltage to the coil *asu(t)*. From circuit analysis of the electromagnet part, we have

$$u(t) = Ri(t) + \frac{d(L(x)i(t))}{dt} \qquad (7)$$

By substituting Eq. (2) into the above Eq. (7), we have:

$$\begin{aligned}\frac{di(t)}{dt} &= \frac{aR + Rx(t)}{aL(0) + L_1x(t)}i(t) \\ &+ \frac{\big(a + x(t)\big)\big(aL(0) + L_1x(t)\big)}{aL_0}i(t)\frac{dx(t)}{dt} \\ &+ \frac{a + x(t)}{aL(0) + L_1x(t)}u(t)\end{aligned} \qquad (8)$$

Eqs. (6) and (8) describe the mathematical model of Magnetic Levitation system. This model is used for simulation of the response of the physical system. Before the simulation of the system we determine the specific coefficients used in the model. These coefficientsare chosenfrom a real existing system [15] and represented in Table 1.

By using the coefficients in Table 1, the magnetic levitation system is simulated in MATLAB. Fig. 1 shows simulator is used for applying our method of control to the MagLev system.

Table 1. Constant coefficients.

Description	Symbol	Value	Unit
coil inductance	L(0)	2×10^{-3}	H
coil resistance	R	0.8	Ω
mag. inductance	L_0	16.7×10^{-3}	H
mag. ind.coeff.	a	1.18	m
mass of object	m	4.16×10^{-3}	Kg

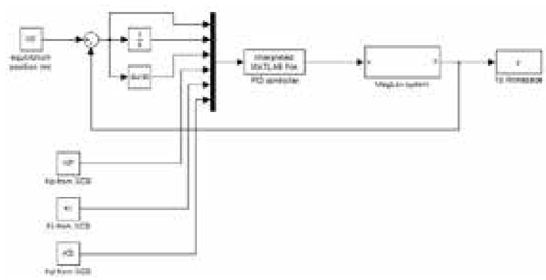


Fig. 1. Simulation of the MagLev system.

III. XCS (ExTENDED CLASSIFIER SYSTEM)

The XCS is a rule-based system in which each rule has a condition, action and set of parameters: prediction, fitness, prediction error and experience. The complete set of rules form the population. The rules whose conditions match the input data form a match set. In the match set each rule has an action and the different actions available in the match set, form the action set. A roulette wheel mechanism is used to choose an action. Then the action is sent to the environment and according to the system response a reward is received. Reinforcement learning is applied to the action set to update the parameters according to the reward. A genetic algorithm runs on the population to guide the search for better rules. XCS learns repeatedly in order to evolve the rule population [16, 17].

Step1. XCS initialize the population with 2000 rules randomly. The condition part of each rule is the position of ball and the action is the PID gains.

Step2. At each stagethe system receives the ball position as an input and forms the match set

[M].

Step3. If [M] contains less than θ_{min} mindifferent actions covering classifiers are created with a condition that matches the current input and a random action is selected from among those not in [M]. Specially, each attribute in the condition of covering classifier is set to # with a probability of $P_{\#}$ and to the corresponding input symbol, otherwise.

Step4. For each action a in [M], XCS computes the system prediction *P(a)*, which is an estimate of the payoff that the system expects when action a is performed. It is computed by the fitness-weighted average of all matching classifiers that specify action *a*.

$$p(a) = \frac{\sum_{cl.a=a \wedge cl \in [M]} cl.p \times cl.F}{\sum_{cl.a=a \wedge cl \in [M]} cl.F} \qquad (9)$$

where cl.a is the action, *cl.p* is the prediction and *cl.F* is the fitness of classifier *cl.* The different values of *P(a)* form the prediction array. XCS selects an action by roulette wheel mechanism and the rules that indicate the selected action form the action set.

Step5. XCS selects a classifier from the action set by a fitness-proportionate roulette wheel. The selected classifier is sent to the environment.

Step6. At the end of each stage, the position of ball is considered as the initial position for the next stage and steps 1 to 5 are repeated.

Step7. After five stages, the overall response is compared with the system that is tuned by ISE method. If two response parameters, settling time and overshoot, was enhanced, the reward *R* is returned to the five selected classifiers.

Step8. The experience of selected classifiers is updated as follows:

$$exp \leftarrow exp + 1 \qquad (10)$$

XCS uses the reward *R* to update the parameters of the selected classifiers. Initially, the classifier prediction is updated as follows:

$$\begin{cases} p \leftarrow p + \dfrac{R-p}{exp} & if\ exp < \dfrac{1}{\beta} \\ p \leftarrow p + \beta(R-p) & otherwise \end{cases} \qquad (11)$$

where β ($0<\beta<1$) denotes the *learning rate*. Next, the prediction error is updated:

$$\begin{cases} \varepsilon \leftarrow \varepsilon + \dfrac{(|R-p|-\varepsilon)}{exp} & if\ exp < \dfrac{1}{\beta} \\ \varepsilon \leftarrow \varepsilon + \beta(|R-p|-\varepsilon) & otherwise \end{cases} \qquad (12)$$

The update of classifier fitness *F* is slightly more complex. First, the classifier *accuracy κand* the classifier relative *accuracy κ'* are computed as

$$\kappa = \begin{cases} 1 & if\ \varepsilon < \varepsilon_0 \\ \alpha\left(\dfrac{\varepsilon}{\varepsilon_0}\right)^{-\upsilon} & otherwise \end{cases} \qquad (13)$$

$$\kappa = \begin{cases} 1 & if\ \varepsilon < \varepsilon_0 \\ \alpha\left(\dfrac{\varepsilon}{\varepsilon_0}\right)^{-\upsilon} & otherwise \end{cases} \qquad (14)$$

The parameter ε_0 ($\varepsilon_0>0$) controls the tolerance for prediction error ε; the parameter α ($0<\alpha<1$) and the parameter υ ($\upsilon>0$) are constants controlling the rate of decline in accuracy κ when ε_0 is exceeded. If the prediction error ε is below the threshold ε_0 the classifier is said to be accurate (it has accuracy=1); otherwise, the accuracy κ drops off quickly, dependent on the values of α and υ. The accuracy values of the rules in the action set of each stage are used to calculate relative accuracy κ'. Finally, classifier fitness is updated toward the classifier's current relative accuracy as follows:

$$F \leftarrow F + \beta(\kappa' - F) \qquad (15)$$

Step9. If the average time since the last GA to the classifiers exceeds a threshold θ_{GA}, a GA is applied to the set of classifiers which formed the action set in each stage. The GA selects two parental classifiers with probability proportional to their fitness inversely. Two offspring are generated by crossing and mutating the parents. Two classifiers with highest experience and lowest fitness are deleted from the population and the offspring are inserted to the population.

IV. RESULTS AND SIMULATION STUDY

The mathematical dynamic model of the magnetic levitation system as well as the PID controller has been developed in MATLAB Simulink for simulation. The K_p,K_i and K_d parameters of the PID controller which used in the Simulink have been generated by using the MATLAB programming (XCS algorithm). The XCS-PID system use five different PID controllers for one initial situation. These PID controllers are selected among of hundreds of PID controllers which have maximum strength.

To adjust classical PID controller gains, ISE criteria is used. Due to this criteria PID gains are chosen as K_p=1455, K_i=2314 and K_d=26 for the MagLev system. These gains are constant along the whole ten 10 second simulation and for every initial situation. Response of the MagLev system with this PID controller for four different initial situations is shown in Figs. 2-5. Subsequently we run our XCS algorithm offline, then we used the attained PID controllers for our simulation and the consequent responses will be shown for the same initial situations. The system simulation with the XCS-PID tuning shows smaller overshoot and better settling time rather to ISE-PID.

In the first simulation, we put the levitation mass5 centimeters below the solenoid. Responses of the ISE-PID and XCS-PID systems will be shown by dashed lines and solid lines respectively in the figures. Parameters of the five rules chosen for the controller are listed in Table 2.

Table 2. Parameters of chosen rules in five stages

N	Rule	Strength	Prediction	Error	Experience
1	636	731.99772	50	2.00e-323	14930
2	1122	623.81954	50	2.00e-323	12570
3	737	392.19494	50	2.00e-323	13719
4	309	385.12840	50	2.00e-323	13564
5	347	425.14672	50	2.00e-323	13823

And so on for three another initial situations we used same approach and the figures will show performances.

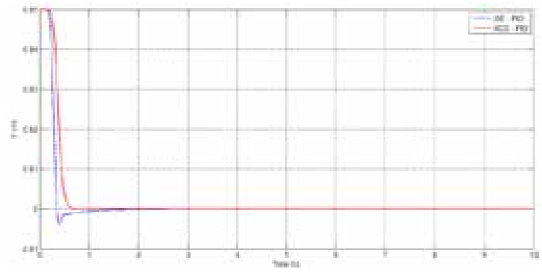


Fig. 2. The levitaion mass control by using ISE criteria (dashed line), settling time is 0.7112 (s) and overshoot is 7.5153%. and by using XCS algorithm (solid line) settling time is 0.5782 (s) and overshoot is 0.0605%.

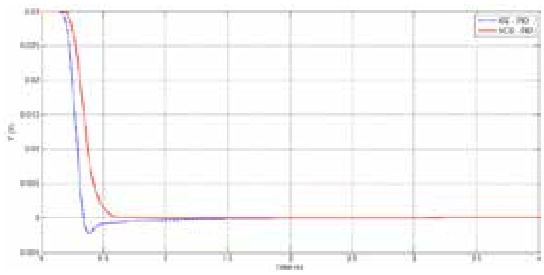


Fig. 3. The levitaion mass control by using ISE criteria (dashed line), Settling time is 0.6902 (s) and overshoot is 7.0263%. and by using XCS algorithm (solid line) settling time is 0.5484 (s) and overshoot is 0.0543%.

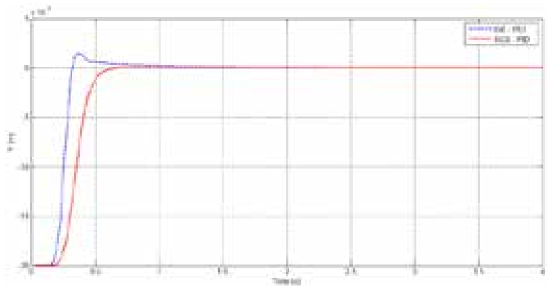
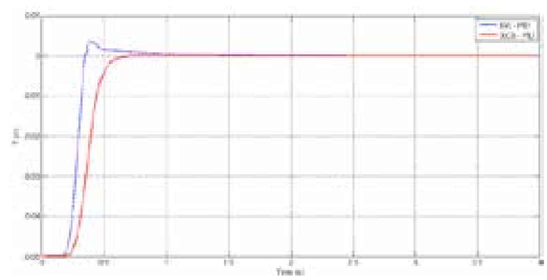


Fig. 4. The levitaion mass control by using ISE criteria (dashed line), Settling time is 0.6514 (s) and overshoot is 7.5935%. and by using XCS algorithm (solid line) settling time is 0.5619 (s) and overshoot is 0.0757%.



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V. CONCLUSION

An eXtended Classifier System (XCS) was presented which was used to tune the PID controller parameters offline. The PID controller was then applied to control the ball position in a magnetic levitation system. During the training phase, the PID parameters were selected by the XCS system according to the ball position. The closed loop response of the presented method was compared with the system in which the PID parameters were tuned by integral of squared of error (ISE) criteria. At the end of training mode, the responses were compared where the XCS system led to a better performance having less overshoot and less settling time.

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