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A NONLINEAR LEARNING CONTROL APPROACH FOR A CEMENT MILLING PROCESS

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Abstract. In this paper, a novel parameter tuning strategy for a class of controllers is discussed. The mathematical background of the algorithm is based on variable structure systems theory, which is well known with its robustness to systems having uncertainties and imprecision in the representative model. Since the course of modeling is concerned primarily with the dominant behavior, the nonlinearities existing in the system dynamics, external disturbances and plant-model mismatches require the control engineers to design controllers, which adapt the design parameters to alleviate the stated difficulties. The method introduced in this study is applicable to controller structures, whose outputs are linear in the adjustable parameters. In order to demonstrate the performance of the proposed technique, control of a cement milling circuit is studied with time-varying set values, time-varying plant parameters and a considerable amount of observation noise.

Key Words: Industrial Process Control, Sliding Mode Control, Parameter Tuning and ADALINE

1. INTRODUCTION

Nonlinear behavior, uncertainties and the existence of external disturbances constitute the prime difficulties, which are frequently encountered and which are to be alleviated by a suitably designed control strategy. Among many approaches, design based on linearization maintains its popularity since the field of nonlinear control still does not offer systematized procedures. Cement mill circuit discussed in this paper is one particular example revealing a highly nonlinear behavior. The linearization technique for such systems restricts the designer to focus on some predefined operating conditions, i.e. the operating range of the controller gets narrower and another crucial problem arise. Namely, the instabilities that can occur during the transition between local regions of the state space. The solution is either to increase the number of local regions, which increases the computational cost and decreases the realization feasibility, or to use learning control strategies.

In the literature, learning control has widely been studied and numerous works have been presented in connection with VSS based learning design [1-3]. The background of the study in this paper goes firstly to the work presented by Sira-Ramirez et al [1], in which, a sliding mode strategy for adaptive learning in an Adaptive Linear Element (ADALINE) has been discussed. The proposed method has been applied for the inverse dynamics identification of a Kapitsa pendulum by assuming the bounds of uncertainty constant. Yu et al [2] has developed an adaptive uncertainty bound dynamics. In the above mentioned references, the need for the availability of the target signal [1] and due to the noisy observations, the gradually increasing behavior of the uncertainty bound parameter [2] constitute the fundamental problems restricting the physical applicability. In [3], Parma et al propose another technique for using VSS theory in learning. Beyond the need for having the target signal, the method practically suffers from the evaluation of some numerical derivatives. More explicitly, if there is noise on the measured quantities, the user must either filter the signals, which would necessitate a costly hardware, or be confined to noise-free operating environments.

Although there are direct methods for designing the learning strategy, one might focus of the improvements on an existing strategy by utilizing the VSS technique. In [4-5], Efe et al demonstrate that the gradient based strategies can be modeled approximately as dynamical systems and a VSS based stabilization technique can be developed to reduce the marginally stable behavior taking place around origin. In essence, the algorithm presented in [4-5] aims to reduce the noise sensitivity of the gradient techniques. The drawback of what is discussed in these references is the large computational cost.

From this point of view, it should be clear that the quantification of learning, together with strict design considerations is a complex problem, which is not at the stage of analytic generalization. However, in some studies, the qualitative analysis can be incorporated into the design yielding satisfactory results [6].

In this paper, a dynamical model for the learning strategy in the weights of an ADALINE controller is developed. The method is based on the work in [1,6]. The primary difference from [1] is the use for control purpose, and that from [6] is the composition of the input signal driving the controller. Here, the controller is driven by the tracking error, the integral of the tracking error and a constant bias whereas in [6], the derivative of the tracking error is used instead of the integral action.

The organization of this paper is as follows: The following section describes the dynamics of the plant under control. The third section presents the proposed form of the learning strategy. The simulation results are discussed in the fourth section and the concluding remarks are given at the end of the paper.

2. CEMENT MILLING CIRCUIT

A cement milling circuit depicted in Fig. 1 is an industrial process, which takes raw material as input and which produces cement having the desired fineness. The raw material enters to the classifier after grinding process in the mill. The classifier separates the incoming material into two parts. The refused material i.e. the material that is not in the desired fineness is sent back to the mill for regrinding. Accepted material goes to the other stages of the production as the output of the cement milling circuit. The fineness of the output material is adjusted in the supervisory level by setting either the desired product flow rate or tailings (refused material) flow rate and mill load [7-8].

The most common control technique for the cement milling circuit uses the proportional and integral control actions (PI). In this control technique, there are one controller output and one desired controlled variable, which are mostly classifier speed and tailings flow rate respectively. The drawback of such a control method is the fact that there is no control over the feed flow rate and correspondingly on the mill load. In practice, the mill load is an important variable because it determines the energy consumption and the efficiency of the circuit. Moreover, the excess load which is resulted by PI control in the mill causes the interruption of the grinding process.

Another method for controlling cement milling circuits uses the linearized mathematical model of the circuit with two controller outputs (feed flow rate and classifier speed) and two controlled variables (mill load, either product flow rate or tailings flow rate) [7-8]. The problems related to the linearization have already been mentioned.

A recent contribution to the cement milling circuit control focuses on a multivariable nonlinear predictive control technique [8]. Although this technique gives satisfactory performance in terms of robustness and stability, the design of the controller depends strictly on the mathematical model of the plant.

The mathematical representation of the cement milling circuit is described in (1)-(3). Clearly, as given in (4)-(5), the dynamics is highly nonlinear and involve strict interdependencies between the variables.

$$\dot{y}_f = -\frac{10}{3} y_f + \frac{10}{3}(1-\alpha(z,v,d))\varphi(z,d) \tag{1}$$

$$\dot{z} = -\varphi(z,d) + u + y_r \tag{2}$$

$$\dot{y}_r = -100 y_r + 100\alpha(z,v,d)\varphi(z,d) \tag{3}$$

where,

$$\alpha(z,v,d) = \frac{\varphi^{0.8} v^4}{K_\alpha + \varphi^{0.8} v^4} \tag{4}$$

$$\varphi(z,d) = \max\left\{0; (-0.1116dz^2 + 16.5z)\right\} \tag{5}$$

$$K_\alpha = 570^{0.8} 170^4 \left(\frac{57}{45} - 1\right) \text{ (tons/h)}^{0.8} \text{ (r/min)}^4 \tag{6}$$

In these equations, z is the mill load (tons). The variables y_f and y_r represent product flow rate (tons/h) and tailing flow rate (tons/h) respectively. The control inputs to the system are denoted by u and v, which are feed flow rate (tons/h) and classifier speed (r/min) respectively. The hardness of the material in the mill is denoted by d. This quantity can independently vary and its value is determined according to a reference hardness value taken as unity.

Magni et al [8] has developed the model above. In this reference, the model is validated and the responses have comparatively been presented. Briefly, the model validation is made by matching the step responses of the mathematical model and the real system. In the above equations, the dynamics describing the behavior of the mill load, product flow rate and tailing flow rate are stated. The control problem is to maintain a desired mill load together with a desired product flow rate, which are the two of the states selected in this paper and in [8]. It should be noted that the third state variable is automatically determined by the other two. Therefore, the designer might choose the tailings instead of the product flow rate. Since the efficiency of the process in terms of energy consumption and production is dependent on the load on the mill, the mill load must be one of the states that is to be kept under control.

3. NONLINEAR LEARNING CONTROL APPROACH

It should be apparent to the reader that the system described above has two control inputs, and the designer is to come up with two controllers. Since the structures of the controllers are the same in this paper, we present the approach generically.

In this section, it is assumed that the physical constraints on the controller outputs put a bound on adjustable parameter magnitudes ($\|\underline{G}\| < B_G$), time derivative of the input vector ($\|\dot{\underline{\Omega}}\| < B_{\dot{\Omega}}$) and the time derivative of the desired output of the controller ($\|\dot{\tau}_d\| < B_{\dot{\tau}_d}$).

The controller is described in (7), in which the adjustable parameter vector is as described in (8), and the input vector driving the controller is given in (9).

$$\tau = \underline{G}^T \underline{\Omega} \tag{7}$$

$$\underline{G} = \begin{bmatrix} G_p & G_i & G_c \end{bmatrix}^T \tag{8}$$

$$\underline{\Omega} = \begin{bmatrix} e & \int_0^t e(\sigma)d\sigma & 1 \end{bmatrix}^T \tag{9}$$

In above, *e* is the error on the mill load for the first controller. Similarly for the second controller, *e* represents the error on the product flow rate. Defining the error at the output of the generic controller as in (10), one can consider the Lyapunov function in (11) as a suitable function for describing the learning performance. The time derivative of the function is as given by (12).

$$e_c = \tau - \tau_d \tag{10}$$

$$V = \frac{1}{2} e_c^2 \tag{11}$$

$$\dot{V} = \dot{e}_c e_c \tag{12}$$

where,

$$\begin{aligned} \dot{e}_c &= \dot{\tau} - \dot{\tau}_d \\ &= \dot{\underline{G}}^T \underline{\Omega} + \underline{G}^T \dot{\underline{\Omega}} - \dot{\tau}_d \end{aligned} \tag{13}$$

Proposition: For a controller structure described in (7), the adoption of the parameter tuning strategy as in (14) leads to the stability in the sense of Lyapunov.

$$\dot{\underline{G}} = -\frac{\underline{\Omega}}{\underline{\Omega}^T \underline{\Omega}} \zeta \operatorname{sign}(e_c) \tag{14}$$

Proof: If (14) is substituted into (13), the error dynamics in (15) is obtained. Using the bounds of the uncertainties mentioned at the beginning of the section leads to (16).

$$\dot{e}_c = -\zeta \operatorname{sign}(e_c) + \underline{G}^T \dot{\underline{\Omega}} - \dot{\tau}_d \tag{15}$$

$$\begin{aligned} \dot{V} &= -\zeta |e_c| + \left(\underline{G}^T \dot{\underline{\Omega}} - \dot{\tau}_d\right) e_c \\ &< \left(B_G B_{\dot{\Omega}} + B_{\dot{\tau}_d} - \zeta\right) |e_c| \end{aligned} \tag{16}$$

In order to have a negative time derivative for the Lyapunov function in (11), the parameter ζ must satisfy the following relation.

$$\zeta > B_G B_{\dot{\Omega}} + B_{\dot{\tau}_d} \tag{17}$$

The analysis presented aims to maintain the negative definiteness of the Lyapunov function in (11), which is an instantaneous cost measure. It is apparent that the use of the presented analysis in control applications entails the desired values of the controller outputs. Therefore, for the applications in which the desired signals are available, the method can easily be used without any modification.

In this part, parallel to the philosophy of variable structure controller design procedure, a switching function is defined and described by (18). The symbol *e* seen in (18) is the discrepancy between the reference state value and observed state value. It should here be noted that since the dynamics under investigation is a first order one, the dimension of the sliding hypersurface is equal to zero, which is apparent from (18).

$$s = e \tag{18}$$

If one replaces e_c of (14) with s of (18), it is possible to prove that the Lyapunov function in (19) is minimized in time and its time derivative is enforced to have negative values due to the adjustment strategy in (14).

$$V = \frac{1}{2}s^2 \tag{19}$$

For this case, the selection of ζ values must be reasonably large for maintaining the sliding motion. The details of the analysis are not included due to the space limit. For an in-depth discussion, the reader is referred to [6].

4. SIMULATION STUDIES

In the simulations, the proposed control strategy has been utilized to produce the desired control inputs. For this purpose, the plant is kept under an ordinary feedback loop. In order to demonstrate the efficiency of the approach, the observed state variables are corrupted by a Gaussian distributed random sequence having zero mean and variance equal to 0.0165. Furthermore, the hardness parameter d has been set to unity until t=2.1h, beyond this time the parameter abruptly jumps up to 1.34. The simulation stepsize has been chosen as 18 seconds, and the final time has been set to 9 hours. The values of the controller parameters and the system states are initialized as follows: $y_f(0)=120$; $y_r(0)=0$; $z(0)=55$; $G_{p1}(0)=-5$; $G_{c1}(0)=-5$; $G_{p2}(0)=10$; $G_{c2}(0)=10$; $e_1(0)=0$; $e_2(0)=0$. The uncertainty bound parameters are selected as: $\zeta_{yf}=12$ and $\zeta_z=17$. In order to reduce the effect of chattering, the sign function has been replaced with a smooth equivalent described as:

$$\mathrm{sign}(x) \approx \frac{x}{|x| + 0.05} \tag{20}$$

In addition to these, the desired value of the mill load (z) is set to 75 tons, and the behavior in Fig. 2 is obtained. The desired value of the product flow rate (y_{fd}) is set to 120 tons/h and the result in Fig.3 is observed. As mentioned earlier, the tailings flow rate (y_r) settles down to the solution imposed by the other two state variables and is depicted in Fig. 4. In Figs. 5-6, the error on the mill load and the error on the product flow rate is illustrated. Clearly, the behavior is convergent and small magnitude deviations occur due to the noise in the observed state variables. Fig. 7 displays the behavior of the applied feed flow rate (u), and the behavior of the applied classifier speed (v) is depicted in Fig. 8. Lastly, the time evolution of the adjustable controller parameters are illustrated in Fig. 9. Note that the parameters evolve convergently and remain bounded.

5. CONCLUSIONS

In this paper, a nonlinear learning control technique is discussed. The method is based on VSS theory, which is well known with its robustness to unmodeled dynamics and disturbances. The proposed scheme has been tested on a validated mathematical model of a cement milling circuit [7-8], which is highly nonlinear, and which has three state variables with two control inputs.

The results presented demonstrate that the proposed technique is useful in control of such complex systems both in the sense of tracking accuracy and in the sense of robustness and computational simplicity.

6. REFERENCES

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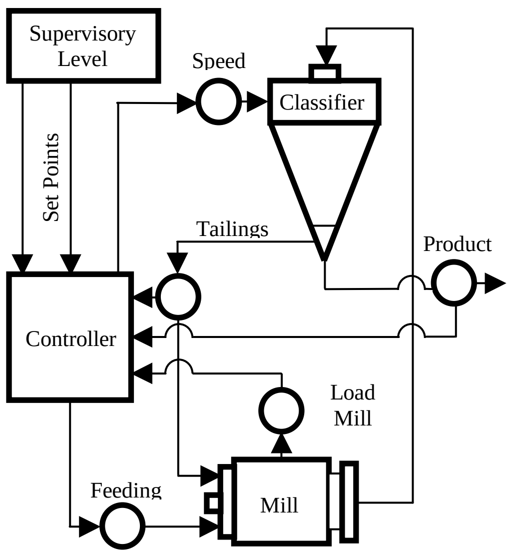

Figure 1. Block diagram of the cement milling circuit

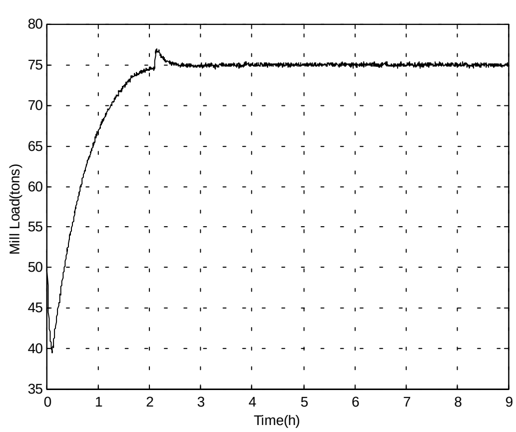

Figure 2. Behavior of the mill load (z)

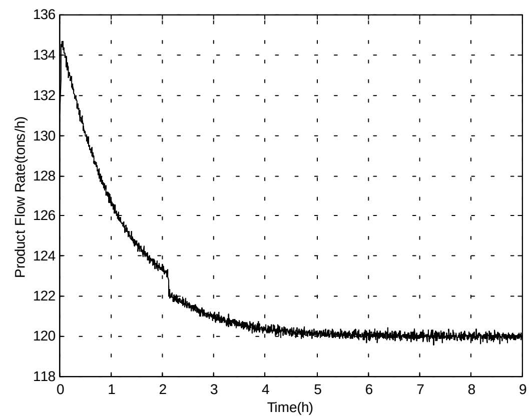

Figure 3. Behavior of the product flow rate (y_f)

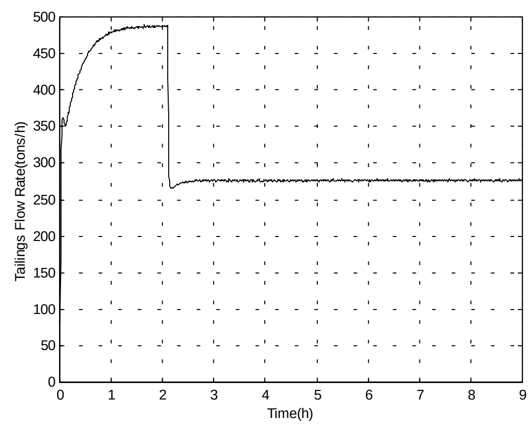

Figure 4. Behavior of the tailings flow rate (y_r)

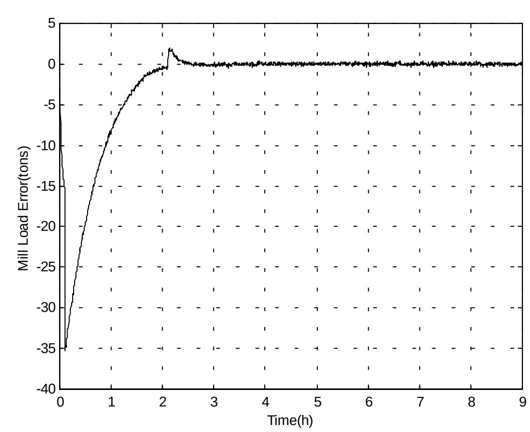

Figure 5. The error on the mill load

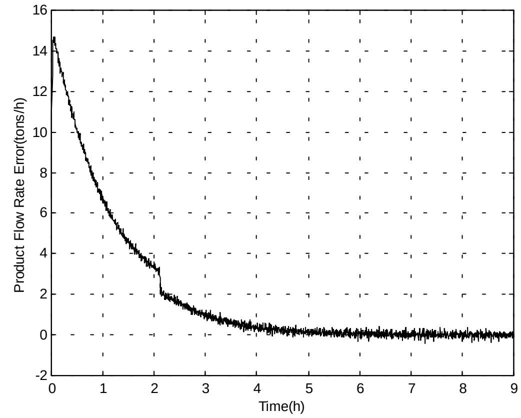

Figure 6. Ther error on the product flow rate

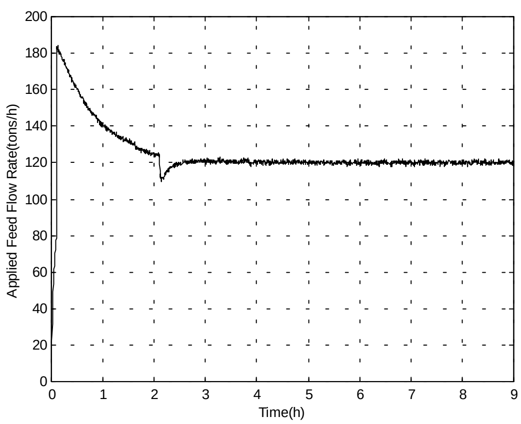

Figure 7. Behavior of the applied feed flow rate (*u*)

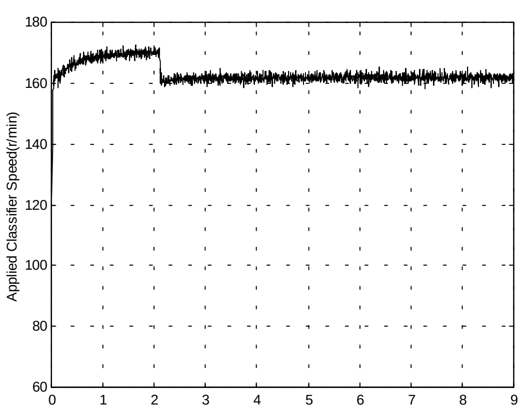

Figure 8. Behavior of the applied classifier speed (*v*)

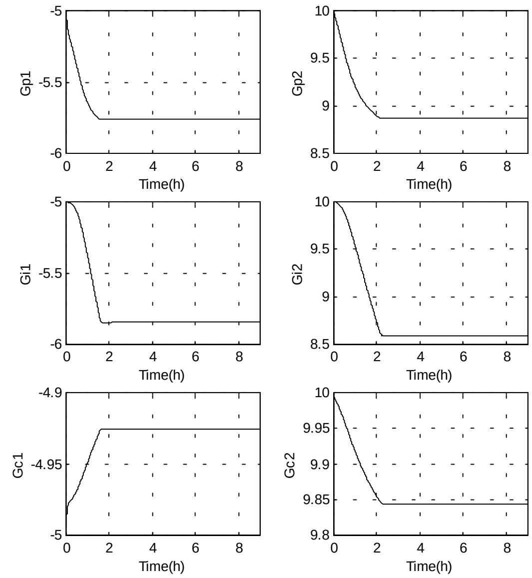

Figure 9. Time evolution of the parameters of the two controllers