Hydraulic Press Commissioning Cost Reductions via Machine Learning Solutions

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Abstract. In industrial processes, PI controllers remain as the dominant control technique due to their applicability and performance reliability. However, there could be applications where the PI controller is not enough to fulfill certain specifications, such as in the force control loop of hydraulic presses, in which specific pressure profiles need to be ensured in order not to damage the workpiece. An Iterative Learning Control scheme is presented as a Machine Learning control alternative to the PI controller, in order to track the pressure profiles required for any operational case. Iterative Learning Control is based on the notion that a system that realizes the same process repeatedly, e.g. hydraulic presses, can improve its performance by learning from previous iterations. The improvements are revealed in high-fidelity simulations of a hydraulic press model, in which the tracking performance of the PI controller is considerably improved in terms of overshoot and the settling time of pressure signal.

Keywords: Hydraulic Presses, Machine Learning, Iterative Learning Control, Force Control

1 Introduction

The main objective of this thesis is to provide Machine Learning (ML) solutions to the control problems that hydraulic presses face nowadays. Modern hydraulic circuit manufacturers face increasingly challenging specifications for their systems, which are required to perform highly accurate control tasks. In the industrial field there is limited work, or just focused on theoretical approaches, that address hydraulic presses control problems with ML algorithms.

The industry processes still maintain the PI controller as the dominant controller as their applicability and performance reliability is well-known for a wide range of operational scenarios. However, there could be applications where the PI controller is not enough to fulfill certain specifications, such as in the force control loop of hydraulic presses, in which there usually exist performance specifications regarding the maximum peak pressure allowed in the cylinder chamber and the settling time of the pressure signal.

ML algorithms are the solution to those cases where the PI controller is not sufficient to meet the workpiece design requirements. By extracting information from previous data, the advanced models based on ML calculate the required control input in order to track the pressure profile for any operational case.

With respect to ML control solutions, there is not an industrial agent nor technological that provide useful and accessible strategies for Machine Tool industrial manufacturers. Therefore, the required degree of development and adaptability of the ML algorithms for its succeeding industrialization and substitution of conventional PI controllers is considerable. The thesis outcomes will not only be substantial in the technical field but will also satisfy the industrial necessity that currently is not being fulfilled.

The present thesis will be carried out in Ikerlan Technology Research Centre in collaboration with FAGOR ARRASATE press machines manufacturer, as well as with the academic assistance of the University of the Basque Country.

2 Techniques improving PI controllers

Several theoretical studies have been carried out in order to improve the performance of a PI controller in hydraulic circuits. These approaches have their foundation on model-based control designs which allow the possibility of using techniques such as feed-forward (FF), feedback or feedback-linearization (FL).

In [12], the modeling of the fundamental dynamics of a linear servo-valve is carried out. Based on this model, the velocity feedback with proportional control loop is used in the position control to achieve higher control bandwidth. The velocity feedback was tested theoretically in a fifth order linear state space, for which the proportional controller and the velocity feedback are sufficient for its control. If the controller is implemented in a nonlinear hydraulic circuit, due to its operation points variation, it will not be efficient.

FF to improve the tracking performance of a PI controller was also used in [16], for a first-order and a fourth-order system with dead time. As the authors pointed out, this technique will not achieve satisfactory results if the model suffers from significant uncertainties, resulting in a highly model-dependent approach.

A comparison between different model-based control approaches for the force control system of a hydraulic actuator was carried out in [5]. They concluded that the best results were given by combining state estimate feedback, output unity feedback, and a velocity FF loop. The approaches were based on the modeling of a linearized state space model, which holds the same model-depending drawbacks as the aforementioned designs.

The improvement of the press behavior with respect to the application of model-based techniques, such as FF and FL, is significant as long as there is detailed information about the particular dynamics of each press. Nevertheless, it is not always possible to achieve a high-level reference tracking performance with the aforesaid control approaches, due to uncertainties existing in the system e.g., model inaccuracy, unmodeled dynamics, disturbance in the systems or parameter variations.

The model accuracy remains as the main difficulty when implementing FF, which appears impracticable without the help of algorithms that allow the possibility of learning model inaccuracies automatically i.e., ML techniques. The estimation of those model inaccuracies could be carried out via ML techniques such as Support Vector Regression, Neural Networks or Gaussian processes. Furthermore, common estimation algorithms used in control systems could be used such as Kalman Filters or state observers. These techniques are expected to be analyzed throughout the thesis, however, in the immediate future, other control techniques are deemed to be more practical for industrial applications.

As an alternative to the aforementioned control techniques and based on automatic learning, as hydraulic presses perform the same process repeatedly under the same operating conditions, Iterative Learning Control (ILC) is proposed. An extra FF signal will be introduced in the system based on ILC which will eliminate the need to know explicitly the system parameters to carry out a perfect pressure reference tracking.

3 Iterative Learning Control

ILC is founded on the concept that a system can improve its performance by learning from previous operations. In this way, as iterations go on the error between the desired pressure reference and the pressure signal will decrease towards a zero error reference tracking.

ILC was first proposed for improving the reference tracking of a system that follows a specific trajectory by Uchiyama in [7]. It was further extended in [2], for a mechanical robot operation. The learning control scheme proposed by Arimoto was:

$$U_{j+1}(s) = U_j(s) + L(s)E_j(s), \tag{1}$$

which is a general past-error FF update law. $L(s)$ is the learning function and determines how the derivative of the tracking error is used to update the control signal from one iteration to the next, as it is explained in [8]. $U_j(s)$ is the Laplace transform of the entire input vector at the j-th learning iteration. The iteration error $E_j(s)$ is given by the difference between the reference and the corresponding iteration output, $E_j(s) = R(s) - Y_j(s)$.

A sufficient condition for the stability of the designed ILC was shown in [3], which guarantees the system stability and monotonic convergence of the error, $E_j(s) = 0$, if:

$$|1 - G(jw)S(jw)L(jw)| < \frac{1}{Q(jw)} \qquad \forall\omega \in [-\infty, \infty]. \tag{2}$$

where $S = \frac{1}{1+GC}$.

There are a set of postulations that need to be satisfied in order to the algorithm proposed by Arimoto to work, which are depicted in [1]. Under these assumptions, the system output would converge into the desired output trajectory as the number of iterations approaches infinity, i.e. $\lim_{j\to\infty} Y_j = R$.

The advantages of ILC are significant:

- By satisfying the design conditions postulated by Arimoto, the ILC will find the optimal input to the system. Although the conditions for perfect reference

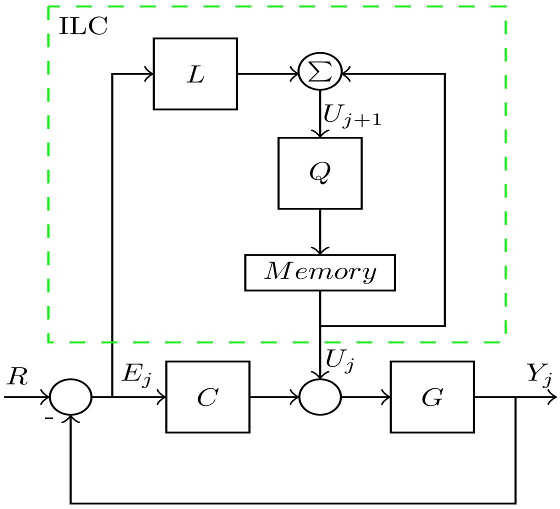

Fig. 1. Parallel ILC scheme.

tracking could always not be achieved, as long as the ILC algorithm remains stable the system will converge monotonically and minimize the tracking error.
– ILC can handle model inaccuracy, unmodeled dynamics or noise in the system and still converge to the desired trajectory. Furthermore, if there is a dynamical characteristic variation in the model, it will progressively adapt to this change by correcting the input at every iteration.
– By designing the learning gains Q and L adequately, ILC guarantees the monotonic convergence condition, which will prevent the system from becoming unstable when ILC is applied.
– The ILC FF signal can be removed at any time, returning to the already existing control.

3.1 ILC in hydraulic presses

ILC algorithms have already been used for solving control problems related to hydraulic presses where the controller cannot track the desired position or pressure reference accurately. ILC in the position control loop of a hydraulic cylinder was first introduced by [4]. At the first 40 iterations, the iteration error converged towards zero, but it remained constant without converging further for subsequent iterations.

An ILC based on linearized state space equations was proposed and implemented in the position control circuit of a hydraulic bench test in [10]. The design of the learning filter was based on the approximated inversion of the plant and showed a non-monotonic behavior at the first iterations that lead the tracking error to increase significantly. In order to eliminate the non-monotonic behavior a forgetting modifying factor was introduced, which is adjusted by trial and error. This hand tuning is indeed what it is desired to avoid as everything should be automated in the press control.

The forgetting factor was also included in [17] to reduce the initial tracking error and accelerate the convergence rate. The factor was included in a PD-type ILC algorithm multiplying the initial control input, and its weight was reduced as the number of iterations rose. The analysis was carried out theoretically for the position control loop and the final result showed that, even with a low trajectory varying reference, the tracking error was significant with the ILC implementation.

Fuzzy ILC algorithms have been also studied for hydraulic circuits, some remarkable studies are [11, 6, 18, 13], in which the learning gains were adaptively adjusted with fuzzy logic. Fuzzy strategies could be of use if expert knowledge is available, however, they hold the same drawback as PI controllers where manual tuning is required in the implementation, which is time-consuming due to the large variety of possibilities to design the fuzzy strategies.

ILC has been implemented either on systems with a limited frequency spectrum or on systems with narrow operating scenarios and without settling time requirements. So far, the ILC algorithm design has not been oriented to an industrial application such as hydraulic presses, where simple control structures with fast converging times are required. In this thesis, an ILC algorithm will be designed and implemented in a hydraulic press to improve the existing PI controller scheme and be able to satisfy the most challenging design specifications.

4 System Model

A hydraulic cushion circuit consists of several components such as pipelines, proportional valves, hydraulic cylinders, non-return valves or accumulators. However, in the force control, the elements that take part in the control are the cylinder and the proportional valve. The proportional valve´s opening ratio is modified so that the desired pressure in the cylinder is achieved, which is the signal to be controlled in the force circuit.

During the drawing process of a hydraulics press, i.e. when the slide makes contact with the cushion, a positive input signal u is sent to the valve, in order to connect port A with T and port P with B (see Fig. 2). At this valve arrangement, oil is led through the valve from the cylinder to the tank, retracting the cylinder's piston.

Once the drawing process is finished, the cylinder's piston needs to be extended to its initial position to start the press cycle again. By sending a negative input signal to the valve, port B connects with T and port P with A. At this valve arrangement, no oil will flow through the valve as ports P and B are closed. Extending the piston to its initial position requires that the pressure introduced by the pump to be considerably larger than the maximum pressure expected at the cylinder chamber.

The relationship between the pressure in the cylinder, the volumetric flow into it and piston motion is as follows:

$$q = A\dot{x} + (V_{\mathrm{d}} + Ax)\beta\dot{P}. \tag{3}$$

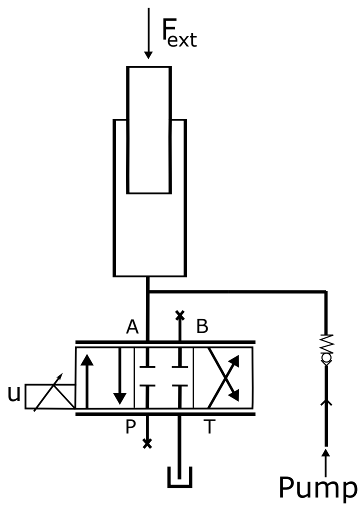

Fig. 2. Hydraulic force control circuit.

Parameters A, V_d and β correspond to the piston area, the dead volume of the cylinder chamber and the hydraulic fluid compressibility, respectively. Variables x and P are the piston position and the cylinder pressure, respectively.

Equation 4 shows the relation between the pressure in the cylinder and the volumetric flow out of the valve

$$q = -K_\mathrm{v}(y_\mathrm{v})\sqrt{P}. \tag{4}$$

$K_\mathrm{v}(y_\mathrm{v})$ is the valve coefficient introduced by [9], here referred to as hydraulic conductance, which is a function of the valve's spool position y_v. The hydraulic conductance function is nonlinear and it is often obtained via empirical tests. Although the estimation of $K_\mathrm{v}(y_\mathrm{v})$ could be done via the ML algorithms listed in section 2, it has been left out for the second part of the thesis.

Ideally, the dynamics of the valve would be negligible as they are faster than any other system component dynamics. However, y_v is the valve response to an input command signal, u. For illustrative purposes, the dynamics of the proportional valve from u to y_v can be regarded (see [14]) as a second-order transfer function:

$$G_\mathrm{v}(s) = \frac{y_\mathrm{v}(s)}{u(s)} = \frac{\omega_\mathrm{n}^2}{s^2 + 2\omega_\mathrm{n}\zeta s + \omega_\mathrm{n}^2}. \tag{5}$$

The following values have been set for the valve parameters: $\omega_\mathrm{n} = 400\,\mathrm{rad/s}$ and $\zeta = 1$. These values are used in simulations in order to analyze the performance of the hydraulic cushion system with the designed control scheme. However, in the design of the control scheme will not be considered as they are approximated values.

5 Controller design

As explained in section 1, PI controllers are the most common controllers used in hydraulic presses to regulate the valve's opening ratio and, therefore, be able to follow the desired pressure reference. Nevertheless, the hydraulic cushion circuit is nonlinear and the PI parameter tuning is confined to a local operating point, resulting in poorer response when the process deviates from this operating point.

In [15], the controller scheme designed for the hydraulic cushion circuit is explained, which consists of a PI controller in combination with feed-forward (FF), feedback linearization (FL) and ILC. FF and FL are used to eliminate the velocity disturbance and minimize the non-linearities in the system, respectively. These two control approaches require full system parameter information which, in the case of the hydraulic cushion system, we do not hold. To counteract the system uncertainties, ILC is introduced which implicitly learns the exact input into the system required for each instant, correcting the model mismatch in the FF and FL. The resulting control diagram is shown in Fig. 3.

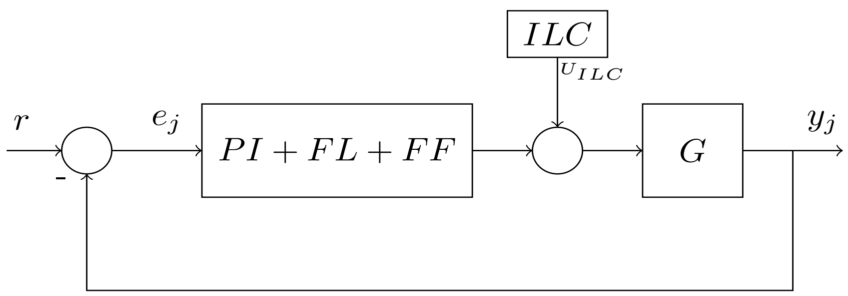

Fig. 3. Block diagram of the resulting control scheme.

5.1 ILC design

From the ILC block diagram shown in Fig. 1, the error propagation equation can be obtained which relates the error at the current iteration with the error at one iteration ahead.

$$E_{j+1}(s) = Q(s)(1 - G(s)S(s)L(s))E_j(s) \tag{6}$$

From Eq. 6, if the L learning filter is designed as $L = C + G^{-1}$, the right hand side of the equation will vanish, resulting in zero tracking error at the second iteration. However, in this design, the inverse of the plant has to be modeled which, if there is uncertainty in the system, will not be simplified.

The unknown parameters corresponding to the proportional valve states, which will affect our plant at high frequencies, are not considered in the L design. Obviously, as some system dynamics are not included in the L filter design, the plant will not be completely simplified in Eq. 6. Therefore, a fourth-order low-pass filter is added in the L learning gain design to attenuate those high-frequencies in which system uncertainty is present.

5.2 Controller implementation

The designed ILC algorithm has been implemented in Simulink's physical component library Simscape. A modified Simscape hydraulic library has been used which has been designed at Ikerlan, called ikSimscape, to carry out the modeling of industrial components and reduce the computational cost that Matlab's Simscape library requires.

The components are parametrized with data-sheet information to obtain the non-linear model of a hydraulic cushion. The parameter information has been obtained from the data-sheets provided by FAGOR ARRASATE.

The model generated by ikSimscape library allows the possibility of reproducing high precision non-linear hydraulic effects. Therefore, if the ILC algorithm is validated in simulations, it is expected to have similar results in a real press.

Figure 4 shows a Simulink model of a hydraulic cushion consisting of a hydraulic cylinder and a proportional valve.

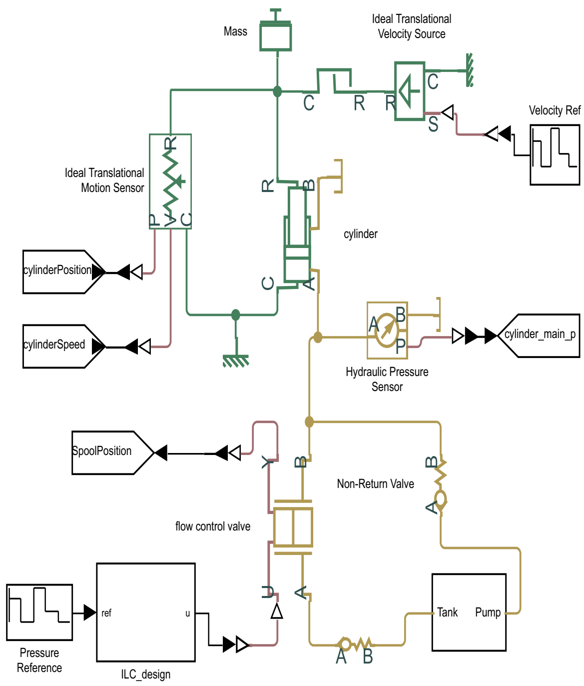

Fig. 4. Simscape implementation of a hydraulic cushion circuit.

6 Simulations

Two pressure reference scenarios have been considered in the simulation so that the designed ILC can be validated in more than one operating point. No velocity disturbance FF signal has been included in the simulations, as it is desired to analyze the ILC performance in the absence of velocity disturbance FF.

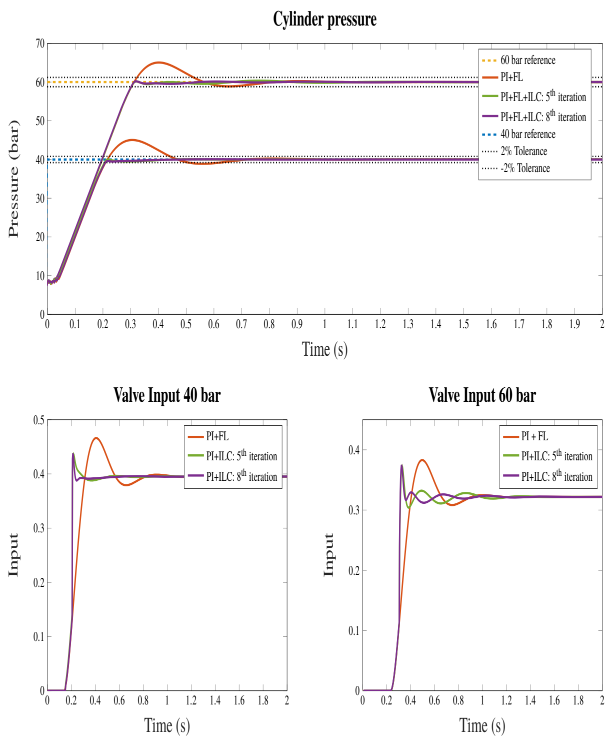

Fig. 5. Pressure reference and control input for 40 bar and 60 bar step response.

At iteration number eight (see Fig. 5) the pressure references are tracked accurately without overshoot. Indeed, the overshoot that exists with the combination of PI+FL controllers disappears as the ILC learns implicitly the exact valve opening ratio required for each instant, which results in no overshoot in the pressure.

The performance specifications with respect to the peak pressure allowed in the cylinder chamber and the maximum settling time of the pressure signal can be observed in Fig. 6.

Figure 6 shows the settling time to within 2% of the final value (marked by a black dotted line in Fig. 5) and the peak pressure over eight iterations for 40

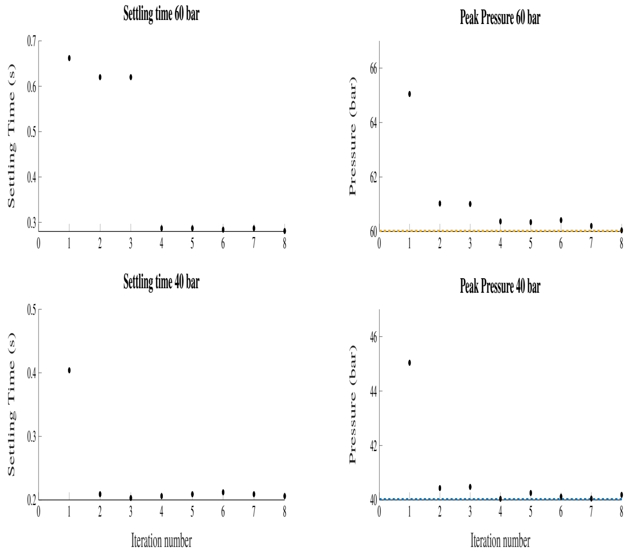

Fig. 6. Settling time and peak pressure of the high fidelity model.

bar set-point. The convergence of the overshoot to 40 bar and 60 bar is reached at iteration number four and continues at the same peak level as iterations go by. The settling time is reduced by more than half in both cases compared to the first iteration where only PI and FL are used. Note that it is physically impossible to reach the desired pressure in less than 0.2 ms and 0.3 ms for 40 bar and 60 bar step reference respectively.

7 Conclusions

An Iterative Learning Control (ILC) algorithm combined with a classical PI controller, feedback linearization (FL) and feed-forward (FF) for the hydraulic cushion circuit has been designed. FF and FL have been included to improve the PI controller reference tracking, however, these are model-based approaches which result in poor response when uncertainty is present in the system.

To counteract the missing system information ILC is included as an extra feed-forward signal in the system. The design is based on the known system parameters and a fourth-order low-pass filter is added to the design in order to attenuate the unknown high-frequencies of the valve.

The designed ILC algorithm has been implemented in a high-fidelity model of a hydraulic press. Different pressure scenarios have been considered in order to validate the algorithm at different working operations. Simulation results show that the designed control scheme considerably improves the reference tracking in comparison to PI+FL control.

8 Future work

Three steps are considered fundamental for the final implementation of the ILC algorithm in a real hydraulic press.

First, the ILC algorithm has to be validated for a wide range of pressure references and for different velocity references in ikSimscape Simulink. The higher the velocity reference is, the bigger the overshoot at the pressure reference tracking will be, therefore a more precise ILC will be required.

Secondly, after testing the ILC in a simulation environment the algorithm will be integrated in a Hardware in the Loop (HiL) platform. This procedure allows to replicate the commissioning process in laboratory environment, due to the fact that controllers are tested against a digital model simulated in Real-Time.

Finally, it is expected to have the controller validated at Ikerlan's HiL platform in order to, subsequently, implement it in a real hydraulic press for the manufacturer FAGOR ARRASATE.

Acknowledgments

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