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Model-based and model-free learning strategies for wet clutch control

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ABSTRACT

This paper presents an overview of model-based (Nonlinear Model Predictive Control, Iterative Learning Control and Iterative Optimization) and model-free (Genetic-based Machine Learning and Reinforcement Learning) learning strategies for the control of wet-clutches. The benefits and drawbacks of the different methodologies are discussed, and illustrated by an experimental validation on a test bench containing wet-clutches. In general, all strategies yield a good engagement quality once they converge. The model-based strategies seems most suited for an online application, because they are inherently more robust and require a shorter convergence time. The model-free strategies meanwhile seem most suited to offline calibration procedures for complex systems where heuristic tuning rules no longer suffice.

1. Introduction

Wet clutches are commonly used in automatic transmissions for off-highway vehicles and agricultural machines to transfer torque from the engine to the load. By disengaging one clutch and engaging another, different transmission ratios can be realized. When a clutch engagement is requested, an operator expects a fast response without vibrations. The torque transfer should thus begin as soon as possible without introducing torque discontinuities and peaks. These machines are operated through several years and under varying environmental conditions such that clutches undergo significant amount of wear and tear, thereby making the clutch control a challenging industrial problem [1]. Contrary to wet-clutches, modeling and control of dry-clutches has received considerable attention in research, often considering a stick–slip hybrid model for analysis. A slip control using linear quadratic regulator with force on clutch piston as input is developed in [2]. While [3] concluded that an online MPC scheme for clutch control is not practically implementable due to the high computation costs, an explicit Model Predictive Control is derived in [4], using a linear cost function for slip control, amongst others. The representative work on wet-clutch includes optimal control of automotive transmission clutch filling [5], PID control for a wet plate clutch actuated by a pressure reducing valve [6], predictive control of a two stage actuation system using piezoelectric actuators for controllable industrial clutches [7], predictive control of an electro-hydraulic actuated wet-clutch for automatic transmission [8] and fast and smooth clutch engagement control for dual-clutch transmissions [9].

The two main challenges for wet clutch control are (i) the intrinsic complex, nonlinear behavior [10], and (ii) the variation of these dynamics over time due to changes in load, oil temperature and wear [11]. When similar or repetitive operations have to be carried out, e.g. the successive engagements of a clutch, learning can be introduced to address these issues. By gradually improving the performance with respect to the previous trial, the complex system behavior can be learned at the cost of a convergence period, and it also becomes possible to automatically adapt to variations in the system's behavior or operating conditions.

In this paper, the potential of several model-based (Nonlinear Model Predictive Control (NMPC), Iterative Learning Control (ILC) and Iterative Optimization (IO)) and model-free (Genetic-based Machine Learning (GA) and Reinforcement Learning (RL)) learning strategies are analyzed for the control of a wet clutch engagement. The model-based approaches rely on a model of the clutch dynamics to update the control signals at each engagement, while in contrast, the model-free ones omit this model and directly explore the input space of possible clutch control signals using a guided trial-and-error procedure, attempting to maximize the reward/fitness.

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The remaining content of this paper is laid out as follows. Section 2 briefly describes the wet-clutch dynamics and objectives. Sections 3 and 4 introduce the model-based and model-free learning techniques respectively, and illustrate their application to wet clutch control. Section 5 details the experimental results followed by a comparison of their benefits and drawbacks in Section 6. Section 7 finally concludes the paper.

2. The wet-clutch

A wet clutch is a device which is used to transmit torque from one shaft to another by means of friction force. As illustrated in Fig. 1, it contains two sets of friction plates, one that can slide in grooves on the inside of the drum, and another that can slide in grooves on the outgoing shaft. Torque can be transferred between the shafts by pressing both sets together with a hydraulic piston, which can be realized by sending an appropriate control signal to the servovalve in the line to the clutch. Initially, during the filling phase, the clutch chamber fills up with oil and the pressure builds up, until it is high enough to compress the return spring and accelerate the piston. When the piston advances far enough and presses the plates together, the filling phase ends and the slip phase begins. During the slip phase, torque is transferred, so that the difference in the angular speeds between the shafts starts to change. This difference in angular speeds is called the slip speed, and will be shortened to slip in the remainder. This slip decreases until both shafts have the same rotation speed. A dynamic model of a hydraulic multi-plate clutch actuator controlled by an electro valve with internal pressure feedback [12] or a model based on power oriented graphs [13] have been reported in literature. However, it has been argued that, it is frequently unfeasible to transfer these models to other applications because of major modifications that would be needed [8]. Building on this argument, the work in this paper either uses simple system identified models or model free control approaches.

So far, the goals for the control were not strictly defined. In general, we want both a fast and smooth engagement. As a measure for this smoothness, we use the highest absolute value of the second derivative of the slip (the jerk), since it is strongly related to the experienced operator comfort [14]. For a given engagement duration, we then want to find the control yielding the lowest absolute value of jerk. This can be realized by a short filling phase (without torque transfer) followed by a smooth transition into the slip phase (buildup of torque), after which the load has to be synchronized further, still in a smooth manner (significant torque transfer).

To validate the developments an experimental setup is used, where an electromotor (30 kW) drives a flywheel (2.5 kg m^2) via a torque converter and two mechanical transmissions, as shown in Fig. 2. The controllers are applied to the first range clutch of the left transmission while the right transmission is used only to vary the load observed by the first transmission and to apply an adjustable braking torque. The controlled transmission is equipped with sensors measuring the speeds of the different shafts and the pressure of the oil in the line to the clutches. An additional torque

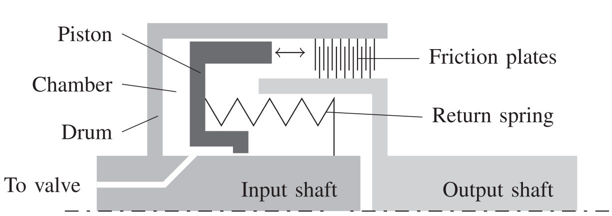

Fig. 1. Schematic overview of a wet-clutch and its main components.

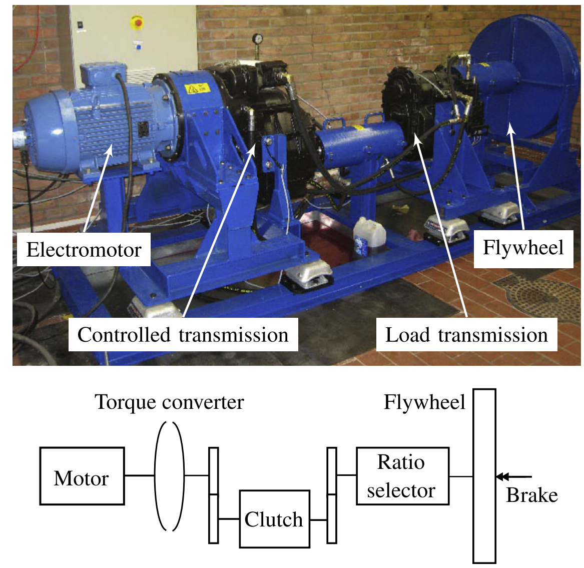

Fig. 2. Experimental setup with wet clutches.

sensor is installed to illustrate the performance, but it is not used for the control itself. All experiments are performed with a fixed engine speed, while the output starts at standstill and is then accelerated by engaging the clutch for first gear in the controlled transmission. The initial conditions are zero current and atmospheric pressure. A dSPACE 1103 board is used to control the setup. The entire wet-clutch dynamics is subjected to the following physical constraints:

$$
\begin{aligned}
&0 \leqslant \mathit{Current}\ (\text{Amps}) \leqslant 0.8 \\
&0 \leqslant \mathit{Pressure}\ (\text{Bars}) \leqslant 14 \\
&0 \leqslant \mathit{Slip}\ (\text{normalized}) \leqslant 1.
\end{aligned} \tag{1}
$$

Clearly, the outlined goals are qualitative and therefore to realize them as parametric trajectories, an element of learning is necessary for the control of wet-clutches. This motivates us to integrate learning in model-based controllers or to develop completely model-free learning strategies.

3. Model-based learning control

This section discusses three model-based learning techniques for wet clutch control. A two-level learning control scheme based on NMPC is presented first, followed by a similar two-level control scheme using ILC instead of MPC. Afterwards, the IO technique is presented as an alternative.

3.1. Two-level NMPC (2l-NMPC)

For the wet clutch with its nonlinear transitions between two phases, it is difficult to develop a single performant control algorithm. We therefore propose to use separate controllers for each phase. This simplifies the control design, but also the identification, since a model for each phase separately is sufficient instead of a global model. To further reduce the complexity, we only consider tracking controllers. For the clutch, we then have a first controller aiming to track a pressure reference in the filling phase, which is deactivated once the slip phase begins, at which point a second controller is activated to track a slip reference.

MPC is a form of control in which the current control action is obtained by solving on-line, during each sampling period, a finite horizon open-loop optimal control problem taking into account