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A reference free iterative learning strategy for wet clutch control

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***Abstract*— This paper presents a new iterative learning strategy to control wet clutches. These are complex hydraulic systems that are commonly used in automatic transmissions of heavy duty vehicles, and their control aims at performing fast and smooth engagements. Learning is used to overcome the need for complex models and to maintain performance despite large variations in the system behavior. Classical iterative learning control techniques can however not be employed directly since reference trajectories corresponding to the performance requirements are unavailable. Instead, the presented iterative learning strategy translates the performance requirements directly into an objective function and constraints, hence constituting a numerical optimization problem. After each engagement, this problem is solved in order to find the control signal for the next engagement, using a piecewise linear model for the clutch. Learning is included by using the measured response data to update the models and constraints used by the optimization problem.**

The presented strategy is successfully validated on an experimental test bench containing wet clutches. The learning process is shown to converge towards the desired engagement quality, and a demonstration is given of the robustness with respect to changes in the operating conditions.

I. Introduction

Many mechatronic applications are characterized by complex, non-linear behavior. An extensive effort is then required to derive accurate models for the purpose of control. When the behavior also changes over time, the models have to be extended to account for this, or some tuning of the controllers is needed to maintain robust performance.

When similar or repetitive operations have to be carried out, learning can be introduced to address these issues. By gradually improving the performance with respect to the previous trial, good results can be obtained at the cost of a convergence period.

It also becomes possible to operate during normal machine operation, and automatically correct for variations in the system behavior [1]. However, typical learning techniques such as iterative learning control (ILC) focus on improving tracking control, and are of little use when no appropriate reference trajectories for the measured variables are available. Other techniques can be applied in these situations, by parameterizing the control signal and then learning the best parameter values using methods from machine and reinforcement learning. However, since these techniques are often model-free, long convergence periods can be required. In addition, it is difficult to guarantee the performance during this time, which is a disadvantage when the controllers have to learn online.

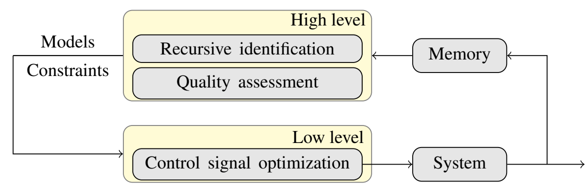

Fig. 1. Presented two-level control scheme: At the high level, the models and constraints for the optimization problem are updated after each engagement. At the low level, these are used to optimize the control signal for the next engagement.

This paper considers the control of wet clutches. These are mechanical devices often found in transmissions of heavy duty applications, used to engage or disengage the load from the engine. They are a good example of the mechatronic applications described above, with non-linear and time variable dynamics. Their behavior also exhibits two distinct phases, each with different dynamics. For such a clutch, the goal is to engage as fast as possible, without causing discomfort for the operator. Since good reference trajectories corresponding to these specifications are unavailable, classical learning techniques are difficult to implement. In this paper an alternative approach is presented which uses the performance specifications directly in order to formulate a numerical optimization problem. Before each engagement, this problem is solved to determine the control signal, using a piecewise-linear model. Numerical values are assumed to be known for the variables at the transitions and for all other constraints. The optimized control signal is then applied to the system, and the measured response is used to adapt the models and constraints before the next control signal is calculated. This results in a two level control structure, as illustrated in figure 1, with the optimization procedure on the low level, being fed models and constraints by recursive estimators and learning laws on the high level.

The remainder of the paper is organized as follows: First, wet clutches and their control are discussed in section II. Next, more details on the different elements of the presented strategy and their application to clutches are given, with a discussion on the optimization procedure, the recursive model estimation, and the learning laws for the constraints in sections III, IV and V respectively. Section VI presents an experimental validation of the learning strategy on a wet clutch system. Finally, section VII ends the paper with some conclusions and suggestions for further work.

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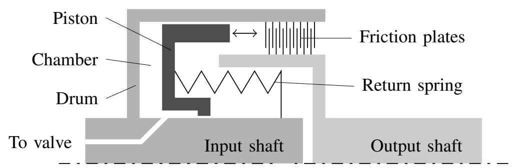

Fig. 2. Schematic representation of a wet clutch and its components.

II. WET CLUTCHES

Wet clutches are mechanical devices commonly found in automatic transmissions of heavy duty applications. When engaged, they connect the shafts from the engine and the load and transfer power between them by means of friction. As illustrated in figure 2, a first set of friction plates is attached to the ingoing shaft via the drum while a second set of plates is attached to the output shaft. Both sets are free to translate axially, and can be pressed together by a hydraulic piston. In order to engage it is thus required to increase the pressure in the clutch chamber by controlling the current to the electromechanical servovalve. The clutch and supply line then fill up with oil and the pressure increases until it is high enough to overcome the return spring force. As a result, the piston starts to move towards the plates. During this first part of the engagement, called the filling phase, no torque is transferred. This only commences once the piston makes contact with the plates. The clutch then enters the slip phase, as the slip, defined as the difference in rotational speeds between the shafts, decreases. When the pressure is high enough the output shaft is accelerated until it rotates synchronously with the input, and the slip reaches zero.

The requirements for a good wet clutch engagement are two-fold. Firstly, the driver expects to get a response as fast as possible. To this end, the output shaft has to start accelerating and torque transfer has to begin as soon as possible. Secondly, to avoid severe discomfort when the load is accelerated it is required to obtain smooth profiles for the torque and slip, and low absolute values of the jerk [2]. Sending the maximal control current to the servovalve then becomes impossible, as brutal, uncomfortable engagements would be obtained. Instead, during the filling phase, when the piston is traveling freely and no torque is transferred, it is desired to move the piston very rapidly to a position just before the friction plates. Before contact is made, it has to be slowed down, and during the remainder of the engagement the current has to be regulated carefully to ensure a smooth engagement.

There are three main difficulties when controlling wet clutches. First off, their dynamic behavior is non-linear and difficult to model accurately. During an engagement, two distinctly different phases can be observed, with a non-linear transition between the two. Even within each phase, the dynamics remain non-linear due to phenomena like flow through small orifices, non-linear springs, friction, etc. A second issue is the strong variation of the dynamics over time, due to wear and variations in operating conditions like the load and oil temperature. This varying behavior makes robust control of wet clutches a challenging problem [3]. A last difficulty for clutch control is the lack of a piston displacement sensor. The presence of such a sensor would simplify the control considerably, as reference trajectories for the piston displacement can easily be derived and the use of feedback or ILC [4] then becomes possible. Typical transmissions however are only equipped with pressure gauges in the line to the clutch, and incremental encoders to measure the rotational speeds of the shafts.

Wet clutch control has already been studied by several authors. Some have derived full physical models and applied them to the design of feedback controllers in [5], [6], [7] and feedforward controllers in [8], [9]. To cope with the non-linear behavior at the transition from filling to slip, [6] uses fixed feedforward signals to bring the clutch into the slip phase, before activating a feedback controller. While this already reduces the complexity of the required models, a considerable amount of online tuning is still necessary to guarantee good performance under all operating conditions. In a previous work by the author [10], these issues are already addressed using a learning technique similar to the presented one. However, only the filling phase of a clutch engagement was considered. In order to optimize the entire engagement, this is now extended to both phases, significantly adding to the complexity of the controller. In addition, a more complete and formal description of the control strategy is given.

III. LOW LEVEL: OPTIMIZATION PROBLEM

In order to apply the proposed control approach to a wet clutch engagement, a numerical optimization problem has to be defined. The goal is to minimize the time required before the load is synchronized, without exceeding a given value of the jerk and without violating any other constraints. To bypass the difficulties related to the transition between filling and slip phases, the problem is reformulated slightly. First, the time is minimized required to reach a transitional state, at which the clutch makes contact with the plates. Next, starting from this state, the remaining time before the load is completely synchronized is minimized as well. A good value of this transitional state is learned by the high level learning law discussed in section V. In order to solve the optimization problem, several models are required to simulate the system behavior. A first set of models relate the control current u to the measurable pressure p and normalized slip s, with separate models for the filling and slip phase respectively. The estimation of these models is discussed in section IV. Since the piston displacement z is not measurable, section V discusses another iterative technique to estimate this model.

As the problem is solved numerically, the duration of the control signal before the transition is reached can be denoted by its number of samples K_1, and the duration of the following synchronization can be denoted by K_2. The optimization problem then has as its goal to minimize the sum $K = K_1 + K_2$ in order to minimize the total engagement time. Since K_1 and K_2 are not known beforehand, they are variables for the optimization problem. As this results in a non-convex problem that is difficult to solve, some reformulations are introduced. The first is a feasibility search which is performed to find K_1 [11]. For a fixed duration K_1, it is checked if the problem can be solved and solutions exist. If so, K_1 is reduced, otherwise it is increased. Using a bisection algorithm the lowest value K_1^* can then be found by solving a limited number of simpler subproblems. The value of K_2 is also not minimized directly, but a different workaround is utilized. A fixed time horizon K_2^* is considered, sufficiently large to ensure load synchronization can be obtained without violating the system constraints, and the weighted sum of the absolute differences between the slip and zero is minimized. The optimization problem thus attempts to get the slip to zero as fast as possible.

This results in a series of convex optimization problems that have to be solved. Each has a different K_1 but the same large value of K_2^*, and is given by

$$\min_{u(:),x(:)} \sum_{k=1}^{K} \Big(\big|s(k) - 0\big| \; + \; \beta\big|u(k+1) - u(k)\big|\Big), \quad \text{(1a)}$$

s.t.

$$x(k+1) = A_1 x(k) + B_1 u(k), \quad k = 1 : K_1 - 1, \quad \text{(1b)}$$

$$\begin{pmatrix} p(k) \\ z(k) \end{pmatrix} = C_1 x(k) + D_1 u(k), \quad k = 1 : K_1 - 1, \quad \text{(1c)}$$

$$\dot{z}(K_1 - N) \leq \epsilon, \quad \text{(1d)}$$

$$z(K_1 - N) = z_{final}, \quad \text{(1e)}$$

$$p(K_1) = p_1, \quad \text{(1f)}$$

$$x(k+1) = A_2 x(k) + B_2 u(k), \quad k = K_1 : K, \quad \text{(1g)}$$

$$\begin{pmatrix} p(k) \\ z(k) \\ s(k) \end{pmatrix} = C_2 x(k) + D_2 u(k), \quad k = K_1 : K, \quad \text{(1h)}$$

$$\left|\begin{matrix} \dot{s}(k) \\ \ddot{s}(k) \end{matrix}\right| \leq \begin{pmatrix} \dot{s}_{max} \\ \ddot{s}_{max} \end{pmatrix}, \quad k = K_1 : K, \quad \text{(1i)}$$

$$s(k) \geq 0, \quad k = K_1 : K, \quad \text{(1j)}$$

$$u_{lb} \leq u(k) \leq u_{ub}, \quad k = 1 : K, \quad \text{(1k)}$$

$$y_{lb} \leq Cx(k) + Du(k) \leq y_{ub}, \quad k = 1 : K. \quad \text{(1l)}$$

As explained, the cost function (1a) penalizes the difference between the slip and zero. Also added is a regularization term with a small weight β, introduced to avoid excessive spikes in the control signal. The dynamics for the first phase without torque transfer are described by A_1, B_1, C_1 and D_1 in (1b) and (1c), while A_2, B_2, C_2 and D_2 in (1g) and (1h) do the same for the second phase. To obtain a good transition between the two, (1d) and (1e) force the piston to slow down before making contact with the plates, a fixed number of samples N before the transition. At the transition itself the pressure is constrained by (1f) such that enough force on the plates is built up to transfer a significant amount of torque. Next, constraints (1i) and (1j) are included to ensure the slip decreases as fast as possible with limited jerk. Constraints (1k) and (1l) finally provide upper and lower bounds during both phases for the current, pressure and position.

The resulting optimization problems (1) are linear and can be solved with standard solvers. In this paper MOSEK is used to solve the series of problems is in less than 1 s. However, since the problems are solved in between engagements no attempts have been made to further reduce the calculation time.

IV. High level: Recursive model estimation

Models need to be supplied to the low level optimization problem, such that the output variables can be predicted for a given control input. To avoid having to derive complex and accurate models a priori, a recursive estimation scheme is employed. After each engagement the batch of measured data is used to update the model parameters, while also taking into the account the previous models. The estimation is performed using data measured online, using real control signals. As a result, simplified models with limited ranges of validity can be tuned to predict the behavior precisely for these types of control signals, and yield a good prediction accuracy. If needed, a piecewise structure can be used, using a succession of simplified models instead of a single more complex one.

In this section, models for the pressure and slip are discussed, as sensors are available to compare the predicted variables with the measured ones. This is not the case for the piston displacement, which is modeled in a different way discussed in section V. For the recursive estimation of the pressure and slip models, many different techniques and model structures can be used. Most existing recursive estimators however are aimed at calculating a single parameter update after each sample. In those cases the dataset is typically very small, while the available timeframe to find the update is very short. In the proposed situation an entire batch of data is available after each iteration, and plenty of calculation time before the next iteration. With this in mind, a novel batch recursive estimator for discrete time output error models has been derived in [10]. It has similar properties to the regular recursive output error estimator described in [12]. The main difference is that many consecutive parameter updates are calculated for each batch of data instead of just one. An improved convergence rate is thus obtained at the cost of an increase in computational load.

This method is applied to the estimation of three different models. A first model predicts the pressure during the filling phase, while the other two predict the pressure and slip respectively during the slip phase. Each of the three estimation algorithms uses only a part of the measured data, corresponding to the conditions under which they will be used to predict the outputs in the optimization problem. The model structures are fixed a priori. In this case, the models are of third order, with the same small delay.

V. High level: Iterative learning laws

A. Iterative learning of position model

Since no position sensor is available, a regular recursive identification of the model relating control current and piston displacement can not be applied. It is however possible to estimate the time when the piston makes contact with the plates, based on a change in the measured rotational speeds when torque transfer commences. This value t_{start} can be

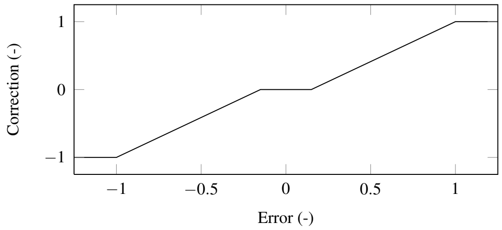

Fig. 3. Dimensionless learning function $\mathcal{C}$ of the high level controller.

compared with the contact time predicted in the optimization, $t^*_{start} = (K^*_1 - N)T_s$. Based on the difference, the position model is then updated such that it manages to predict the contact time more accurately.

In this paper, a model with a first order low pass behavior is used. The pole is fixed at $1\,\mathrm{Hz}$, based on measurements performed on a similar test setup equipped with a position sensor. The gain γ of the model is a variable that is adapted by the high level controller to improve the prediction accuracy, rescaling the model to better correspond to the measured contact time. This is done according to the following ILC-type learning law:

$$\frac{1}{\gamma_{i+1}} = \frac{1}{\gamma_i} + \rho\,\mathcal{C}\Big(\frac{t^*_{start} - t_{start}}{\sigma}\Big). \tag{2}$$

In this equation, $\mathcal{C}$ is a dimensionless saturated function, and ρ and σ are gains used to translate the error in time to a correction on the inverse of the dimensionless gain γ. In this case, $1/\gamma$ is updated instead of γ because $1/\gamma$ can be interpreted as a measure for the travel distance.

The profile of $\mathcal{C}$, shown in figure 3, is chosen to bound the corrections, but also to ensure that small deviations do not lead to unnecessary changes. When γ remains fixed, the control signal for the fist phase remains more or less unchanged, which makes convergence easier for the latter parts of the engagement process.

Since γ can be used to capture both the uncertainty on the travel distance as on the dynamics, z_{final} in (1e) can be chosen freely.

B. Iterative learning of pressure setpoint

When the pressure and position models predict the system behavior sufficiently accurate, the optimized control signal gently brings the piston into contact with the plates at the end of the filling phase. After K_1 samples, constraint (1f) forces the pressure to be equal to the transitional pressure p_1. Here, the value of p_1 is chosen to ensure that the slip phase has certainly begun at this point, and the slip is already decreasing. The slip model in (1h) is then only required to predict the slip during the remainder of the engagement, and the transition can be omitted. This makes it easier to find a simple but accurate model. Therefore, it is chosen to learn the value of p_1, such that the normalized slip already drops down to 0.9 after K_1 samples. The difference between the observed value s_1 and 0.9 is used to update the transitional pressure p_1, using an ILC-type learning law similar to (2):

$$p_{1,i+1} = p_{1,i} + \tau\,\mathcal{C}\Big(\frac{s^*_1 - s_1}{\varsigma}\Big). \tag{3}$$

In this equation, τ and ς are gains that translate the error in slips to a pressure correction in bar. This law ensures that the transitional pressure p_1 is adapted to the load automatically, without measuring the transferred torque. When for example a heavier load has to be accelerated, more torque is needed to get the desired slip reduction, and hence a higher value of the pressure p_1 will be obtained.

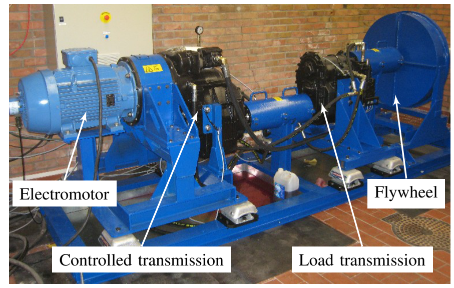

Fig. 4. Test setup: (from left to right) electromotor, controlled transmission, torque sensor, load transmission and flywheel.

VI. Experimental validation

The developed control strategy has been validated on the experimental test bench shown in figure 4. It consists of an SOHB TE10 transmission, containing the wet clutch which is to be controlled. On the left, an induction motor ($30\,\mathrm{kW}$) is connected to drive the system. On the right, the combination of a SOHB RT20000 transmission and a flywheel ($2.5\,\mathrm{kg\,m^2}$) are used to vary the load observed by the controlled transmission. A sensor is installed to measure the transferred torque, but it is only used to illustrate the engagement quality, as this type of sensor is usually not available on industrial transmissions. The experiments are performed with an engine that is controlled at a fixed speed, while at each trial the output is accelerated from zero up to synchronous speed by engaging the clutch for first gear in the controlled transmission. The calculations are performed in MATLAB, using MLIB to communicate with a dSPACE 1103 control board.

A. Performance analysis

In a first run of experiments the operating conditions are fixed to evaluate the learning process and the achieved performance, with the oil cooled to $40\,^\circ\mathrm{C}$ and the observed inertia set to $8.4\,\mathrm{kg\,m^2}$. The control is initialized with suboptimal values for γ and p_1. For the recursive estimators a feedforward engagement is performed, such that a first estimation of the model parameters for all three models can be made. Using these newly estimated models and the initial values for γ and p_1, the first control signal is optimized and applied to the system.

The results obtained after applying this first control signal are shown by the black lines in figure 5, where from

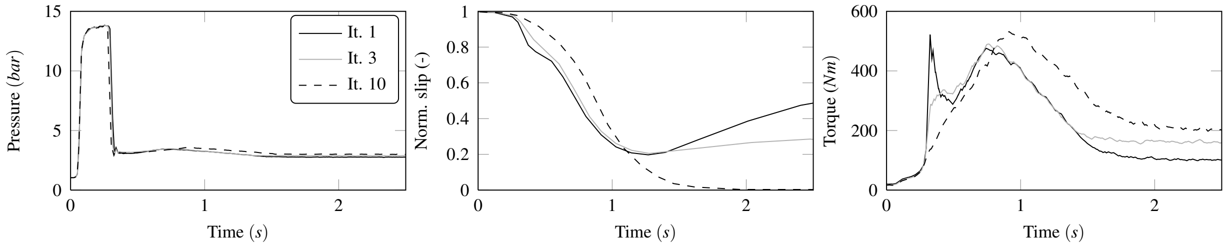

Fig. 5. Improving performance during learning process for engagements with an inertia of $8.4\,\mathrm{kg\,m^2}$ and oil at $40\,^{\circ}\mathrm{C}$. Shown from left to right are the pressure, slip and torque during iterations 1 (black), 3 (grey) and 10 (dashed).

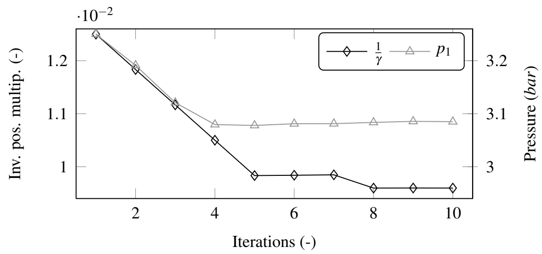

Fig. 6. Evolution of $1/\gamma$ (black) and p_1 (grey) as a function of iterations. Both are iteratively adapted by the high level controller based on the observed performance.

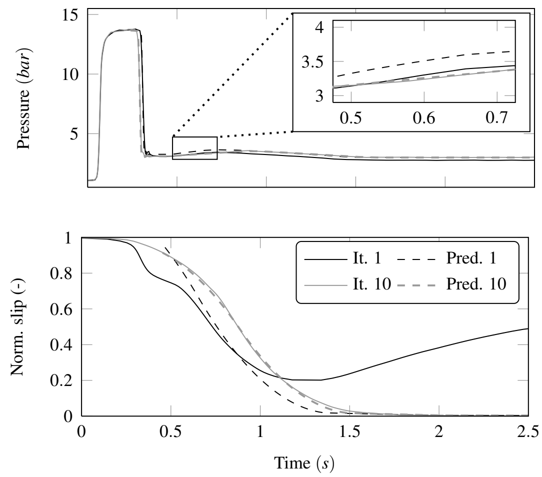

Fig. 7. Increasing prediction accuracy as a function of iterations. The top figure shows the measured and predicted pressures during the 1st (dashed black) and 10th iteration (solid black). The bottom figure shows the same for the measured and predicted slips.

left to right the pressure, slip and torque are shown. The torque rapidly increases to a high initial value, but then dips before it increases again. As a result, the slip changes abruptly yielding a high absolute value of the jerk, and hence discomfort for the operator. Afterwards, the clutch opens again as the pressure is too low and hence the torque is insufficient to synchronize the load.

Over the course of the following engagements the high level controller compensates for this and the performance improves. This is illustrated by the grey lines in figure 5, showing the performance during the 3rd iteration. The torque peak has almost been removed, but the clutch is still not engaging as desired. The dashed lines show the results after 10 iterations, when the learning process has converged. A good engagement quality is now obtained, with smooth profiles for both the slip and torque, ensuring operator comfort without reducing the responsiveness of the system.

One reason for the poor initial performance are the badly selected values for γ and p_1. Figure 6 shows their evolution as a function of the number of iterations. Since the initial value for γ is too low, the true piston displacement is underestimated and the piston has already bumped into the plates before any attempt is made to slow it down. To compensate, the high level controller increases the value of γ such that the piston displacement and the moment when contact with the plates occurs are predicted more accurately. At the same time, the value of p_1 is adapted based on the measured slip, to ensure enough torque is transferred to accelerate the load and reach a slip of 0.9. As can be seen from figure 6, the value of p_1 is reduced, lowering the pressure acting on the friction plates and hence reducing the transferred torque during the initial parts of the engagement. Both parameters converge by iteration 10. This evolution also illustrates the difficulty in choosing good values a priori, as relatively small changes can change the performance drastically.

Another reason for the poor initial performance is the inaccuracy of the models used to predict the pressure and slip. Their first estimate is based on data from a feedforward run, different from the control signals applied after the optimization. The validity of the models is thus limited. The black lines in the top part of figure 7 illustrate this for the pressure, showing a large deviation between the measured (solid) and predicted values (dashed). The accuracy is even worse for the slip, shown in the bottom part of figure 7. Here, the moment when the slip starts decreasing is predicted incorrectly, and consequently the entire predicted profile differs strongly from the measured one. Over the course of the next iterations, the models are re-estimated based on more representative data, and the prediction accuracy increases. When the values for γ and p_1 converge by iteration 10, the conditions for the model estimation remain unchanged and the models converge as well. The prediction accuracy at this time is indicated by the grey lines in figure 7, where the deviations between the measured (solid) and predicted (dashed) values are reduced significantly.

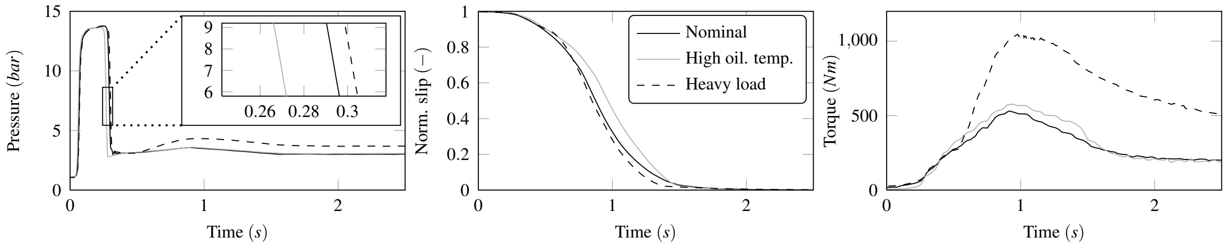

Fig. 8. Demonstration of robustness. The performance after convergence is shown for the test case with an inertia of $8.4\,\mathrm{kg\,m^2}$ and oil at $40\,^{\circ}\mathrm{C}$ (black), an inertia of $8.4\,\mathrm{kg\,m^2}$ and oil at $70\,^{\circ}\mathrm{C}$ (grey) and an inertia of $28.6\,\mathrm{kg\,m^2}$ and oil back at $40\,^{\circ}\mathrm{C}$ (dashed).

B. Robustness analysis

To demonstrate the robustness to changes in the oil temperature and load, two more tests are performed. First, the same load is used but the oil temperature is increased to $70\,^{\circ}\mathrm{C}$. Next, the oil is cooled to $40\,^{\circ}\mathrm{C}$ again but the observed inertia is increased to $28.6\,\mathrm{kg\,m^2}$. The controllers are allowed time to converge and the results after convergence are shown in figure 8. For comparison, the solid black line also shows the performance of the 10th iteration at the fixed conditions of the previous section.

The performance at the elevated oil temperature is shown by the grey lines in figure 8. The main difference with respect to the case at $40\,^{\circ}\mathrm{C}$ is the shorter duration of the high pressure part in the beginning of the engagement. The lower viscosity at higher oil temperatures means the oil flows more easily into the clutch and less effort is required displace the piston. Afterwards, the signals look similar since the amount of flow is small once the piston reaches the plates, and the dependency on the oil temperature is low.

Figure 8 also shows the results of the engagements with the increased inertia. The pressure and torque differ significantly from those with the lower inertia, as more torque is needed to accelerate the larger load, and hence more pressure has to act on the friction plates. In order to compensate, the high level controller automatically increases p_1 and adapts the slip model. As a result, the observed slip profile looks similar to the one at the lower inertia.

VII. Conclusion

This paper proposes an iterative learning strategy for wet clutch control aimed at fast and smooth engagements. The control signals are found by solving an optimization problem of which the objective function and constraints are a direct translation of the performance requirements. After each engagement, the models and constraints are updated using the measured data and the optimization problem is solved again to generate the control signal for the next. This strategy is an alternative to classical iterative learning control, aimed at those applications where the requirements cannot readily be translated into appropriate reference signals or where the required sensors are not available.

An experimental validation is presented, showing how the models and constraints evolve, and how the engagement quality improves as a result. The robustness with respect to variations in the operating conditions is also demonstrated.

In the future, the proposed approach will be applied to gearshifts, where two clutches are controlled simultaneously, such that one engages while another disengages.

Acknowledgment

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