OPTIMAL PIECEWISE-LINEAR CONTROL OF DRY CLUTCH ENGAGEMENT

Alberto Bemporad * **Francesco Borrelli** **
Luigi Glielmo *** **Francesco Vasca** ***

* *Dipartimento Ingegneria dell'Informazione, Università di Siena, Via Roma 56, 53100 Siena, Italy, bemporad@aut.ee.ethz.ch*
** *Automatic Control Laboratory, ETH Zentrum, ETL I 26, 8092 Zurich, Switzerland, borrelli@aut.ee.ethz.ch*
*** *Facoltà di Ingegneria, Università del Sannio, Corso Garibaldi 107, 82100 Benevento, Italy, {glielmo,vasca}@unisannio.it*

Abstract: This paper proposes a novel piecewise linear feedback control strategy for the dry clutch engagement process. Based on a dynamic model of the powertrain system, the controller is designed by minimizing a quadratic performance index subject to constraints on the normal force, normal force derivative, and engine speed. The resulting model predictive controller is shown to consist of a piecewise linear feedback control and can be tuned so that fast engagement, small friction losses and smooth lock-up are achieved. Numerical results show the good performance of the closed-loop system.

Keywords: Automotive control, Automated Manual Transmission, Predictive control, Piecewise linear controllers, Friction.

1. INTRODUCTION

Recently, the engagement control of automotive dry clutches is becoming more and more important, due to the increasing use of automated manual transmission in modern vehicles (Powell *et al.*, 1998). The engagement control of dry clutches must satisfy different and sometimes conflicting objectives: small friction losses, fast lock-up, preservation of driver comfort. To this aim, several control strategies have been proposed in the literature. In (Szadkowski and Morford, 1992) the problem of avoiding the use of throttle during the engagement in diesel engine vehicles is considered. A fuzzy controller is proposed in (Ercole *et al.*, 1999) where the influence of different friction coefficients and vehicle operating conditions is also analyzed. A similar analysis is also carried out in (Hibino *et al.*, 1996) where an H^∞ controller is designed by using a suitably identified dynamic model of the powertrain. The engagement clutch control in parallel hybrid electric vehicles and in heavy duty trucks are considered in (Lee *et al.*, 1998) and (Slicker and Loh, 1996), respectively. In (Ramond *et al.*, 2000) a predictive control strategy for continuous variable transmission has been proposed. In (Glielmo and Vasca, 2000*a*; Glielmo and Vasca, 2000*b*) the authors have proposed a finite horizon Linear Quadratic feedforward-feedback controller as an effective solution for the dry clutch engagement control problem. In that controller, however, the constraints on the control and state variables were not considered explicitly in the solution of the LQ problem. The controller proposed in this paper tries to overcome this limitation by using a Model Predictive Control (MPC) strategy. The controller is designed by minimizing a quadratic performance index (which takes into account the clutch friction losses) subject to constraints on the control variables (the normal force and its derivative), and on the state variables (the engine speed). As it requires a quadratic program to be solved on-line, an MPC controller is clearly prohibitive on standard automotive control hardware. However, in (Bemporad *et al.*, 2000*b*) the authors have shown how to move completely off line the MPC computation effort, by reducing the control law to a piecewise linear affine function of the states. Such a function is computed off-line by using a multiparametric programming solver, which divides the state space into polyhedral regions, and for each region determines the linear gain which produces a control action equivalent to that one of MPC.

The paper is organized as follows. After reviewing the basics of MPC and derive the quadratic program associated to the controller in Section 2, in Section 3 the multiparametric quadratic programming algorithm to obtain the explicit form of the MPC law is summarized. In Section 4 the model of the clutch system is presented. The design of an MPC controller and the analysis in simulation of different controller tunings are detailed in Section 5.

2. MODEL PREDICTIVE CONTROL

Based on the discrete-time version

$$\begin{cases} x_{t+1} = Ax_t + Bu_t, \\ y_t = Cx_t, \end{cases} \tag{1}$$

of the model of the system to be regulated, MPC aims at making the output y_t track the reference trajectory r_t while fulfilling the constraints

$$\begin{cases} y_{\min} \le y_t \le y_{\max}, \\ u_{\min} \le u_t \le u_{\max}, \\ \delta u_{min} \le \delta u_t \le \delta u_{max}, \end{cases} \tag{2}$$

at all time instants $t \ge 0$, where $\delta u_t = u_t - u_{t-1}$ is the increment of the input signal. In (1)–(2), $x_t \in \mathbb{R}^n$, $u_t \in \mathbb{R}^m$, and $y_t \in \mathbb{R}^p$ are the state, input, and output vector respectively, $r_t \in \mathbb{R}^p$, $y_{\min} \le y_{\max}$ ($u_{\min} \le u_{\max}$) are bounds on outputs (inputs), and the pair (A, B) is stabilizable.

Assume that a full measurement of the state x_t is available at the current time t. Consider the prediction error $\varepsilon_{t+k|t} = y_{t+k|t} - r_t$ and the performance index

$$V \triangleq \sum_{k=0}^{N_y-1} \varepsilon'_{t+k|t} Q \varepsilon_{t+k|t} + \delta u'_{t+k} R \delta u_{t+k}. \tag{3}$$

MPC solves the following optimization problem

$$\begin{aligned} \min_{U_t} \quad & \{V(\xi_t, U_t)\}, \\ \text{subj. to } & y_{\min} \le y_{t+k|t} \le y_{\max}, \ k = 1, \dots, N_{cy} \\ & u_{\min} \le u_{t+k} \le u_{\max}, \ k = 0, 1, \dots, N_{cu} \\ & \delta u_{min} \le \delta u_{t+k} \le \delta u_{max}, \ k = 0, 1, \dots, N_{cu} \\ & x_{t|t} = x_t, \\ & x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k}, \ k \ge 0 \\ & u_{t+k+1} = u_{t+k} + \delta u_{t+k}, \ k \ge 0 \\ & \delta u_{t+k} = 0, \ N_u \le k < N_y \end{aligned} \tag{4}$$

where the column vector $U_t \triangleq [\delta u'_t, \dots, \delta u'_{t+N_u-1}]' \in \mathbb{R}^s$, $s \triangleq mN_u$, is the optimization vector, $\xi_t \triangleq [x'_t, u'_{t-1}, r'_t]'$ is the column vector of the quantities available at t, $x_{t+k|t}$ denotes the predicted state vector at time $t+k$, obtained by applying the input sequence $\delta u_t, \dots, \delta u_{t+k-1}$ to model (1) starting from the state x_t. In (4), we assume that $Q = Q' \succeq 0$, $R = R' \succ 0$, $P \succeq 0$, $(Q^{\frac{1}{2}}, A)$ detectable (for instance $Q = C'C$ with (C, A) detectable). N_y, N_u are respectively the output and the input horizons, $N_y \ge N_u$, and N_{cy}, N_{cu} are respectively the output and the input constraint horizons. Note that the optimal control problem in (4) is based on the condition $\delta u_{t+k} = 0$ for $k \ge N_u$, i.e., the control signal is kept constant after N_u steps in the prediction (Rawlings and Muske, 1993).

By substituting $x_{t+k|t} = A^k x_t + \sum_{j=0}^{k-1} A^j B u_{t+k-1-j}$ in (4), the optimization problem can be rewritten in the following compact form:

$$\begin{aligned} \min_{U} \quad & \left\{ V(\xi, U) = \frac{1}{2}\xi' Y \xi + \frac{1}{2} U' H U + \xi' F U \right\}, \\ \text{subj. to } & GU \le W + E\xi, \end{aligned} \tag{5}$$

where $H = H' \succ 0$, and H, F, Y, G, W, E are easily obtained from Q, R, and (4) (as only the optimizer U is needed, the term involving Y is usually removed from (5)), and for notational simplicity we omitted the explicit time-dependence.

Because problem (5) depends on ξ, the direct implementation of MPC would require the *on-line* solution of a Quadratic Program (QP) at each time step. Although efficient QP solvers based on active-set methods or interior point methods are available, computing the input u_t demands significant on-line computation effort, which might be prohibitive on standard low-cost automotive control hardware.

In this paper we circumvent such a computation problem by proposing an alternative way to solve *off-line* problem (5) for all ξ within a given range of values, i.e., by considering (5) as a *multi-parametric Quadratic Program* (mp-QP).

Once the multi-parametric problem (5) has been solved, i.e. the solution $U^*(\xi)$ of (5) has been found, the model predictive controller (4) is available explicitly, as the optimal input δu_t^* consists simply of the first m components of $U^*(\xi)$ and at time t the control

$$u_t = \delta u_t^* + u_{t-1}, \tag{6}$$

is applied as input to system (1).

3. MULTI-PARAMETRIC QUADRATIC PROGRAMMING

In (Bemporad *et al.*, 2000*b*) it was shown that the control law (6), resulting from the solution of the mp-QP problem, is continuous and piecewise affine. To this end, define

$$z \triangleq U + H^{-1}F'\xi, \tag{7}$$

$z \in \mathbb{R}^s$, and transform (5) by completing squares to obtain the equivalent problem

$$\begin{aligned} \min_z \quad & \left\{ V(\xi, z) = \frac{1}{2} z' H z \right\}, \\ \text{subj. to } & Gz \leq W + S\xi, \end{aligned} \tag{8}$$

where $S \triangleq E + GH^{-1}F'$, and $V(\xi, z) = V(\xi, U) - \frac{1}{2}\xi'(Y - FH^{-1}F')\xi$.

The mp-QP problem consists of computing the optimizer $z^*(\xi)$ and the value function $V^*(\xi) = V(\xi, z^*(\xi))$ *for all* possible vectors ξ in a given compact set X. The solution of mp-QP problems can be approached by employing the principles of parametric nonlinear programming, and in particular the first-order Karush-Kuhn-Tucker (KKT) optimality conditions (Bazaraa *et al.*, 1993).

In (Bemporad *et al.*, 2000*b*) it was shown that for each feasible combination of active constraints, the optimal z and Lagrange multipliers λ are uniquely defined affine functions of ξ and are given by

$$\tilde{\lambda} = -(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}\xi), \tag{9}$$
$$z = H^{-1}\tilde{G}'(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}\xi) \tag{10}$$

where $\tilde{\lambda}$, $\tilde{G}, \tilde{W}, \tilde{S}$ correspond to the set of active constraints.

This result characterizes the solution only locally in the neighborhood of a specific ξ. This characterization remains valid as long as the set of active constraints does not change as we change ξ. The set of parameters ξ where this combination of active constraints remains optimal is defined as the critical region CR_0. This region can be characterized easily. Choose an arbitrary vector of parameter values $\xi_0 \in X$ and let (z_0, λ_0) be the corresponding values satisfying the KKT conditions, which are obtained by solving a QP for $\xi = \xi_0$. Then, (9)-(10) can be computed by simply looking at the constraints in (8) which are active at the minimizer z_0, and then building matrices $\tilde{G}$, $\tilde{W}$, and $\tilde{S}$ accordingly. The variable z from (10) must satisfy the constraints in (8), i.e.

$$GH^{-1}\tilde{G}'(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}\xi) \leq W + S\xi, \tag{11}$$

and by KKT conditions the Lagrange multipliers in (9) must remain nonnegative, i.e.

$$-(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}\xi) \geq 0, \tag{12}$$

as we vary ξ. After removing the redundant inequalities from (11) and (12) we obtain a compact representation of CR_0. Obviously, CR_0 is a polyhedron in the ξ-space, and represents the largest set of $\xi \in X$ such that the combination of active constraints at the minimizer remains unchanged. Once the critical region CR_0 has been defined, the rest of the space $CR^{\text{rest}} = X - CR_0$ has to be explored and new critical regions generated. A possible approach for partitioning the rest of the space is proposed in (Bemporad *et al.*, 2000*b*).

The argument (9)–(12) is repeated in each new critical region, until the whole ξ-space has been covered. Then, those polyhedral regions CR_i are determined where the first m components δu_t^* of $U^*(\xi) = z^*(\xi) - H^{-1}F'\xi$ are the same. If their union is a convex set, it is computed to permit a more compact description of the solution and the corresponding control law is continuous and piecewise affine (Bemporad *et al.*, 2000*b*).

4. DRY CLUTCH DYNAMIC MODEL

A possible dynamic model of the clutch system during slipping conditions consists of the following two differential equations:

$$I_e \dot{\omega}_e = T_{in} - b_e\omega_e - T_{cl}, \tag{13}$$
$$I_v \dot{\omega}_v = T_{cl} - b_v\omega_v - T_l, \tag{14}$$

where I_e is the engine inertia, ω_e the crankshaft rotor speed, T_{in} the engine torque, b_e the crankshaft friction coefficient, T_{cl} the torque transmitted by the clutch, I_v the equivalent vehicle moment of inertia (it takes into account the presence of the clutch, the main-shaft, the powertrain and the vehicle), ω_v the clutch disk rotor speed, b_v the corresponding friction coefficient and T_l the equivalent load torque. Equation (13) models the rotation of the crankshaft, whereas (14) models the rotation of the so called clutch disk. The remaining part of the powertrain transmission system is simply modeled through the equivalent vehicle inertia I_v and the load torque T_l. Though equations (13)–(14) do not model in detail the whole powertrain, this model captures the main dynamics of the system under investigation and is simple enough to design a controller through analytical procedures. The clutch torque T_{cl} can be expressed as a function of the normal force F_n applied to the clutch disk as follows:

$$T_{cl} = kF_n \text{sign}(\omega_e - \omega_v) = kF_n, \qquad (15)$$

where $k = \frac{4R\mu_d}{3}$, R is the equivalent disk ratio, μ_d is the dynamic friction coefficient and the assumption $\omega_e > \omega_v$, which is typical during engagement, has been made. When the clutch is engaged, by adding (13) and (14), the dynamic model can be written as

$$(I_e + I_v)\omega = -(b_e + b_v)\omega + T_{in} - T_l \qquad (16)$$

where $\omega = \omega_e = \omega_v$.

The switch from the slipping model (13)–(14) to the engaged model (16) is determined by the equality condition $\omega_e = \omega_v$ with the constraint that the clutch torque is smaller than the static friction torque, so that further slipping is avoided.

5. DRY CLUTCH CONTROLLER DESIGN

5.1 *Model for Control and Parameters*

In system (13)–(14) the engine torque T_{in} and the load torque T_l are modeled as a ramp disturbance and as a step disturbance, respectively, leading to the following state space representation:

$$\dot{x} = \begin{bmatrix} -\frac{b_e}{I_e} & -\frac{k}{I_e} & \frac{1}{I_e} & 0 & 0 \\ -\frac{b_e}{I_e} + \frac{b_v}{I_v} & -\frac{b_v}{I_v} & \frac{1}{I_e} & 0 & \frac{1}{I_v} \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ -\frac{k}{I_e} - \frac{k}{I_v} \\ 0 \\ 0 \\ 0 \end{bmatrix} u, \qquad (17)$$

$$y = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} x, \qquad (18)$$

where $x = [\omega_e,\ \omega_e - \omega_v,\ T_{in},\ \dot{T}_{in},\ T_l]'$ and $u = F_n$. Note that the difference between the two rotor speeds has been considered as a state variable instead of the vehicle speed, since the main goal of the controller will be to ensure a suitable profile to this variable thus guaranteeing a smooth engagement process with small friction losses. Model (17)–(18) is discretized by exact sampling (sampling period 10 ms), which results in a model in the form (1).

The following set of parameters with reference to a medium size car are considered: $I_e = 0.2$ kgm^2, $I_v = 0.7753$ kgm^2, $b_e = b_v = 0.03$ Nms, $k = 0.098$ m.

The MPC controller is based on the optimization problem (4) where $y_{min} = [50, 0]$ rad/s (the minimum engine speed and the minimum slip speed, respectively), $y_{max} = [+\infty,\ +\infty]$, $u_{min} = 0$ and $u_{max} = 5000$ N (the minimum and the maximum values of the normal force), $\delta u_{min} = 0$ and $\delta u_{max} = 80$ N (the minimum and the maximum variations of the normal force at each step), and $Q = \left[\begin{smallmatrix} 0 & 0 \\ 0 & q \end{smallmatrix}\right]$.

In order to estimate $x_3,\ x_4,\ x_5$ and filter noise from the measurements of $x_1,\ x_2,\ u$ the state has been estimated by using the Kalman filter based on the noisy model obtained from (1) by adding process and measurement noises, which are assumed to be independent Gaussian noise vectors with covariance matrices I_6 and $\frac{1}{100}I_2$, respectively.

5.2 *Tuning*

In the first phase the parameters are tuned in simulation until the desired performance is achieved by using Simulink and the MPC Toolbox (Bemporad *et al.*, 2000*a*).

The parameters to be tuned are the prediction horizons N_y, the number of free moves N_u, the constraint horizons N_{cy} and N_{cu} and the weights Q and R. The trade-off between fast engagement, minimum slipping losses, and comfortable lock-up is easily adjustable by opportunely choosing the weights Q and R. N_y, N_u, N_{cy}, N_{cu} are the result of a trade off between controller performance and its complexity in terms of number of regions resulting from the explicit solution.

The following three sets of parameters will be considered and compared:

- Controller 1 : $N_y = 10$, $N_u = 1$, $N_{cy} = 2$, $N_{cu} = 1$, $R = 1$, $q = 2$.
- Controller 2 : $N_y = 10$, $N_u = 1$, $N_{cy} = 2$, $N_{cu} = 1$, $R = 1$, $q = 1.1$.
- Controller 3 : $N_y = 20$, $N_u = 2$, $N_{cy} = 2$, $N_{cu} = 2$, $R = 1$, $q = 0.5$.

The number of regions obtained for the three controllers are 3, 3 and 7, respectively. Note that Controller 3 consists of 7 regions as the number of degrees of freedom N_u and input constraints N_{cu} is increased. In Fig. 1 and Fig. 2 two sections corresponding to the polyhedral partition of Controller 1 and 3 are depicted. In Fig. 1 region #1

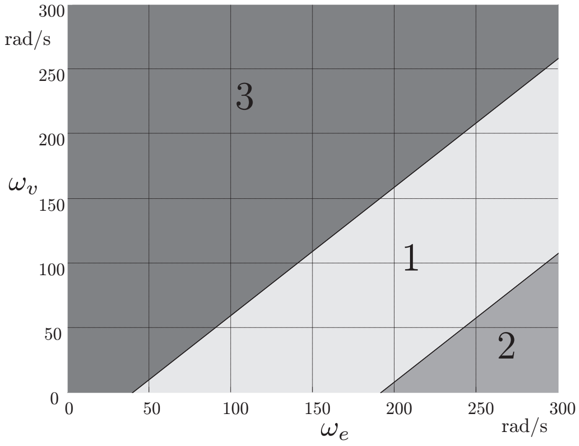

Fig. 1. Controller 1: projection of the critical regions on the $[\omega_e, \omega_v]$-plane (T_{in}=110 Nm, $\dot{T}_{in}$=250 Nm/s, T_l= 4.8 Nm, u=2000 N, r=[0,0] rad/s)

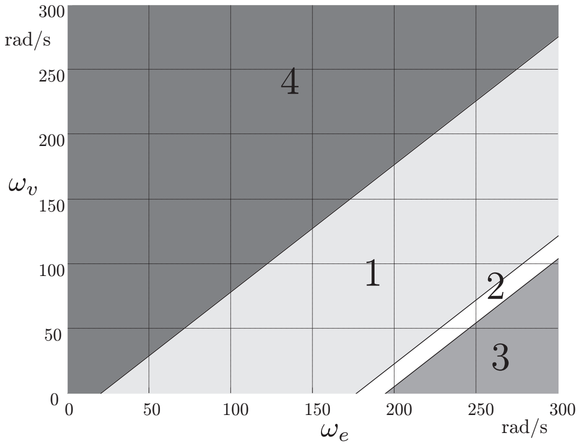

Fig. 2. Controller 3: projection of the critical regions on the $[\omega_e, \omega_v]$-plane (T_{in}=110 Nm, $\dot{T}_{in}$=250 Nm/s, T_l= 4.8 Nm, u=1300 N, r=[0,0] rad/s)

corresponds to the unconstrained linear controller, while regions #2, #3 correspond to the saturated controller at 80 N and 0 N, respectively. In Fig. 2 region #1 corresponds to the unconstrained linear controller, regions #3, #4 correspond to the saturated controller at 80 N and 0 N, respectively, and region #2 is a transition region between the unconstrained and the saturated controller.

5.3 *Simulation Results*

The engagement process during standing starts has been considered. Figures 3-5 show the crankshaft, vehicle rotor speeds and the normal force under the explicit MPC feedback control, for the initial crankshaft speed $\omega_e(0) = 95$ rad/s, $\omega_v(0) = 0$ rad/s.

Each figure refers to a ramp input torque $T_{in} = 100 + 250\tau$ Nm ($\tau \geq 0$ is the time variable expressed in seconds) and a constant load torque $T_l = 4.8$ Nm.

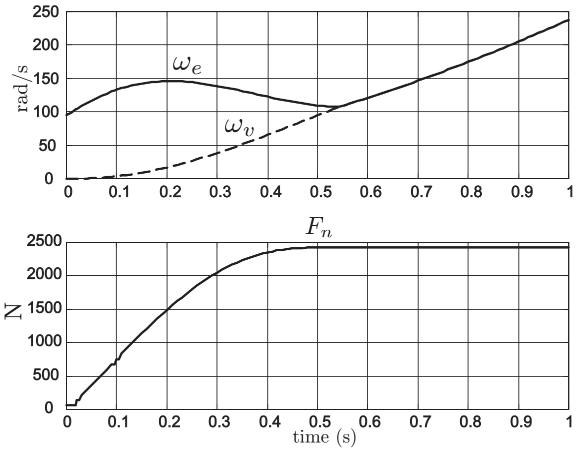

Fig. 3. Crankshaft, vehicle rotor speeds and normal force as a function of time during the start-up engagement process with Controller 1

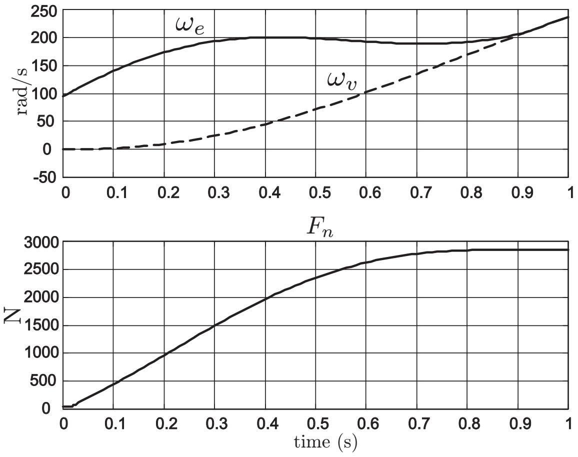

Fig. 4. Crankshaft, vehicle rotor speeds and normal force as a function of time during the start-up engagement process with Controller 2

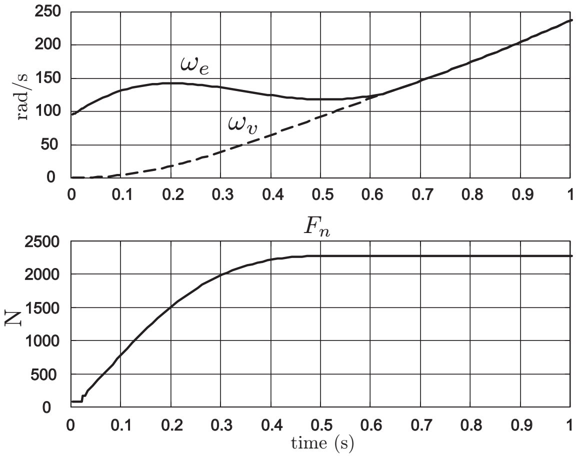

Fig. 5. Crankshaft, vehicle rotor speeds and normal force as a function of time during the start-up engagement process with Controller 3

As proposed in (Glielmo and Vasca, 2000*b*), in order to compare different tunings of the MPC controller, two parameters have been considered: the dissipated energy and the comfort. The former is computed through the expression

$$E_d = \int_0^{\tau^*} kx_1(\tau)x_2(\tau)d\tau, \qquad (19)$$

where τ^* is the engagement time, i.e., the time at which the lock-up occurs. The second comfort-related parameter is the difference $\dot{\omega}_e(\tau^*) - \dot{\omega}_v(\tau^*)$ between the angular accelerations of the two disks at lock-up.

Table 1 summarizes the simulation results obtained with the three different controllers. A comparison between the first two rows of this table shows that by allowing a larger variation of the slip speed (i.e. by selecting larger values for the parameter q) a smaller slip acceleration is obtained at lock-up, which is paid by a larger dissipated energy during the engagement process. Controller 3 seems to provide the best trade-off among the conflicting objectives of the closed loop system. This is justified by the larger number of predictions (i.e. the longer prediction time) exploited by the third controller with respect to the two previous one.

Controller	τ^*	$F_n(\tau^*)$	E_d	$\dot{x}_2(\tau^*)$
1	0.55 s	2418 N	6652 J	320 rad/s^2
2	0.92 s	2846 N	15226 J	126 rad/s^2
3	0.62 s	2258 N	6699 J	134 rad/s^2

Table 1. Performance comparison of the three controllers

6. CONCLUSIONS

A piecewise linear model predictive controller for the dry clutch engagement problem has been proposed. The controller is designed by explicitly considering the input and state constraints in the problem formulation. The direct use of the state variables (engine speed and clutch disk speed) and the estimation of the engine and load torques, allows one to design the controller parameters so that a fast engagement process with small dissipated energy and good comfort can be achieved. Simulation results have shown how to tune the controller parameters so that a suitable trade-off between closed loop performance and controller complexity is achieved. For complex piecewise linear partitions, the authors are currently developing techniques for fast on-line computation based on graph search and envelopes of linear hyperplanes.

7. REFERENCES

Bazaraa, M.S., H.D. Sherali and C.M. Shetty (1993). *Nonlinear Programming — Theory and Algorithms.* John Wiley & Sons. New York.

Bemporad, A., K. Fukuda and F.D. Torrisi (to appear). Convexity recognition of the union of polyhedra. *Computational Geometry.*

Bemporad, A., M. Morari and N.L. Ricker (2000*a*). MPC Simulink Block. Technical Report and software available upon request from the authors. ETH Zurich. Switzerland.

Bemporad, A., M. Morari, V. Dua and E. N. Pistikopoulos (2000*b*). The explicit linear quadratic regulator for constrained systems. In: *Proc. of American Control Conference.* pp. 872–876.

Ercole, G., G. Mattiazzo, S. Mauro, M. Velardocchia, F. Amisano and R. Flora (1999). Co-operating clutch and engine control for servoactuated shifting through fuzzy supervisor. *SAE Technical Paper 1999-01-0746,* pp. 101–109.

Glielmo, L. and F. Vasca (2000*a*). Engagement control for automotive dry clutch. *Proc. of American Control Conference,* pp. 1016–1017.

Glielmo, L. and F. Vasca (2000*b*). Optimal control of dry clutch engagement. *SAE Technical Paper 2000-01-0837,* pp. 1–7.

Hibino, R., M. Osawa, M. Yamada, K. Kono and M. Tanaka (1996). H$^\infty$ control design for torque-converter-clutch slip system. *Proc. of 35th IEEE Conference on Decision and Control,* pp. 1797–1802.

Lee, H. D., S. K. Sul, H. S. Cho and J. M. Lee (1998). Advanced gear shifting and clutching strategy for parallel hybrid vehicle with automated manual transmission. *Proc. of 33rd IEEE Industry Applications Conference,* pp. 1709–1714.

Powell, B. K., K. E. Bailey and S. R. Cikanek (1998). Dynamic modeling and control of hybrid electric vehicle powertrain systems. *IEEE Control Systems Magazine* pp. 17–33.

Ramond, G., D. Dumur and P. Boucher (2000). Application of direct adaptive generalized predictive control to an automatic gear box with a continuous variable transmission. *Proc. of IEEE Conference on Control Applications,* pp. 303–308.

Rawlings, J.B. and K.R. Muske (1993). The stability of constrained receding-horizon control. *IEEE Trans. on Automatic Control,* **38**, 1512–1516.

Slicker, J. and R. N. K. Loh (1996). Design of robust vehicle launch control system. *IEEE Trans. on Control System Technology,* **4**(4), 326–335.

Szadkowski, A. and R. B. Morford (1992). Clutch engagement simulation: Engagement without throttle. *SAE Technical Paper Series 920766* pp. 103–117.