On the Use of Parameterized NMPC in Real-Time Automotive Control

M. Alamir, A. Murilo, R. Amari, P. Tona, R. Fŭrhapter and P. Ortner

Abstract Automotive control applications are very challenging due to the presence of constraints, nonlinearities and the restricted amount of computation time and embedded facilities. Nevertheless, the need for optimal trade-off and efficient coupling between the available constrained actuators makes Nonlinear Model Predictive Control (NMPC) conceptually appealing. From a practical point of view however, this control strategy, at least in its basic form, involves heavy computations that are often incompatible with fast and embedded applications. Addressing this issue is becoming an active research topics in the worldwide NMPC community. The recent years witnessed an increasing amount of dedicated theories, implementation hints and software. The Control Parametrization Approach (CPA) is one option to address the problem. The present chapter positions this approach in the layout of existing alternatives, underlines its advantages and weaknesses. Moreover, its efficiency is shown through two real-world examples from the automotive industry, namely:

- the control of a diesel engine air path and
- the Automated Manual Transmission (AMT)-control problem.

In the first example, the CPA is applied to the BMW M47TUE Diesel engine available at Johannes Kepler University, Linz while in the second, a real world SMART hybrid demo car available at IFP is used. It is shown that for both examples, a suitably designed CPA can be used to solve the corresponding constrained problem while requiring few milliseconds of computation time per sampling period.

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1 Introduction

The last decade witnessed an increasingly rich literature concerning the way NMPC schemes have to be adapted to fit the real-time requirements when applied to fast systems. Among many possible classifications, a straightforward one consists in splitting the approaches into two main categories: The first amounts to bringing the problem into the *linearly hybrid world* while the second keeps handling the *nonlinear* representation of the systems.

Many approaches fall in the first category such as the explicit off-line feedback computation approach based on the Piece-Wise Affine (PWA) approximation [19], the Linear Parameter Varying (LPV) approach [10] using dynamic linearization and the recently developed active set approach for on-line solution of MPC for PWA models [11, 12]. Roughly speaking, these approaches address the real-time requirement by replacing the original problem by a new *and generally different* one which possesses a highly structured form that lends itself to efficient computations[1].

Although these *linearization*-like approaches attempt to solve a modified problem that can be quite different from the original one, they encountered and still have a huge *popularity*. This is based on the belief that the *complete solution* of the original nonlinear constrained problem would be intractable anyway within the available computation time. This difficulty, for a long time considered as insuperable, inspired the idea of *distributing the optimization process over the system lifetime* [1]. Several approaches emerged that implement this simple idea including the multiple shooting real-time iteration [8], the Continuation/GMRES (Generalize Minimum Residual) based differential approach [18] and the Control Parametrization Approach (CPA) [2]. The *philosophy* that underlines the CPA lies in the following ideas:

1. Open-loop control profiles showing very simple time structures, when used in a receding-horizon framework, generally lead to very rich closed-loop control profiles that correspond to a small drop in the overall resulting optimality [4].

2. Although the global optimum of the NMPC cost function corresponding to a low dimensional parametrization is necessarily higher than that of a classical trivial piecewise constant parametrization, for a well designed parametrization however, it is more likely that the former would be easier to achieve than the latter due to the difference in the problem complexity. More clearly, in a constrained computational context, the suboptimal solution of a simple optimization problem may be better than the suboptimal solution of a far more complex one.

3. Classical piece-wise constant control parametrization in which all the control values are degrees of freedom result in unnecessarily high dimensional optimization

[1] It is shown hereafter through the Automated Manual Transmission example that even in the case where the problem can be put in a constrained Quadratic Programming (QP) form, the real-time requirements make it necessary to resort to some kind of dedicated parametrization.

problems. This is *a fortiori* true in the case where even the state values along the future system's trajectory are taken as degrees of freedom. Although these high dimensional problems are highly structured and can therefore be quite efficiently handled by dedicated algorithms, they still need incompressible high demanding preparation steps. Moreover, the dedicated softwares and memory storage needed for such problems are generally incompatible with embedded capacities. This is particularly true in the automotive applications.

There are many other advantages of the CPA such as its ability to explicitly exploit the model structure that is generally strong in electromechanical systems and the possibility to use control parametrization that takes into account the constraints of the problem at the very definition of the parametrization. For a more detailed presentation of these issues, the reader can refer to [2] and the related references.

This paper is organized as follows: First, some definitions and notations describing the control parametrization approach are introduced in section 2. Then two automotive control examples are proposed to illustrate the efficiency of the approach, namely, the diesel engine air path control problem (section 3) and the automated manual transmission control problem (section 4). Finally, the paper ends with a discussion and some concluding remarks.

2 The Parameterized NMPC: definitions and notation

Let us consider a time-invariant dynamic model given in the following general form:

$$x(t) = X(t, x_0, \mathbf{u}) \quad ; \quad x \in \mathbb{R}^n \quad ; \quad \mathbf{u} \in \mathbb{U}^{[0,T]} \quad ; \quad t \leq T \tag{1}$$

where $x(t)$ is the state at instant $t \leq T$ when initialized at $(0, x_0)$ and under the control profile $\mathbf{u}$ defined on $[0, T]$. Let $\tau > 0$ denote some sampling period such that $T = N\tau$. Each map $\mathscr{U}_{pwc} : \mathbb{P} \times \mathbb{R}^n \to \mathbb{U}^N$ defines on $[0, T]$ a parameterized piecewise constant (p.w.c) control profile (with parameters in $\mathbb{P} \times \mathbb{R}^n \subset \mathbb{R}^{n_p} \times \mathbb{R}^n$) such that:

$$\mathbf{u}(t) \ = \ u^{(k)}(p, x) \quad ; \quad t \in [t_{k-1}, t_k] \quad ; \quad t_k = k\tau$$
$$\mathscr{U}_{pwc}(p, x) := \left(u^{(1)}(p, x) \ \dots \ u^{(N)}(p, x)\right) \in \mathbb{U}^N$$

The state trajectory under the p.w.c control profile $\mathscr{U}_{pwc}(p, x_0)$ is denoted hereafter by $X(\cdot, x_0, p)$. More generally, using a straightforward abuse of notation, for each sampling instant $t_j = j\tau$ $(j \in \mathbb{N})$, the notation $X(t, x(t_j), p)$ denotes the state trajectory of the model at instant $t_j + t$ under the p.w.c control profile defined by $\mathscr{U}_{pwc}(p, x(t_j))$ over the time interval $[t_j, t_j + T]$. Recall that the NMPC strategy relies on the solution at each decision instant t_j of an optimization problem of the form

$$\hat{p}(x(t_j)) := arg \min_{p \in \mathbb{P}} \Big[J(p, x(t_j)) \Big] \quad \text{under} \quad C(p, x(t_j)) \leq 0 \tag{2}$$

where $J(p,x(t_j))$ is some cost function defined on the system trajectory starting from the initial condition $(t_j,x(t_j))$ under the p.w.c control profile defined by $\mathscr{U}_{pwc}(p,x(t_j))$. The condition $C(p,x(t_j)) \leq 0$ gathers all the problem constraints defined on the same trajectory including possible final constraints on the state. Classical NMPC formulation states that once *a solution* $\hat{p}(x(t_j))$ is obtained, the first control in the corresponding optimal sequence $\mathscr{U}_{pwc}(p,x(t_j))$, namely $K(x(t_j)) := u^{(1)}(\hat{p}(x(t_j)),x(t_j))$ is applied to the system during the sampling period $[t_j,t_{j+1}]$. This clearly results in the sampled-time state feedback law defined by:

$$K := u^{(1)}(\hat{p}(\cdot),\cdot) : \mathbb{R}^n \rightarrow \mathbb{U} \tag{3}$$

When a system with fast dynamic is considered however, only a finite number $q \in \mathbb{N}$ of iterations of some optimization process $\mathscr{S}$ can be performed during the sampling period $[t_{j-1},t_j]$. This lead to the following extended dynamic closed-loop system:

$$x(t_{j+1}) = X(\tau,x(t_j),p(t_j)) \tag{4}$$
$$p(t_{j+1}) = \mathscr{S}^q\big(p^+(t_j),x(t_j)\big) \tag{5}$$

where $\mathscr{S}^q$ denotes q successive iterations of $\mathscr{S}$ starting from the initial guess $p^+(t_j)$ which is related to $p(t_j)$ to guarantee (if possible) the translatability property (see [2] for more details). The stability of the extended system (4)-(5) heavily depends on the performance of the optimizer $\mathscr{S}$, the number of iterations q and the quality of the model (see [3] for more details).

3 Example 1: Diesel engine air path control

Compared to standard gasoline engines, Diesel engines show better torque characteristics at low speed and reduced fuel consumption. However, the major drawback in such engines is the emission of oxides of nitrogen (NOx) and particulate matter (PM). To this respect, the intake manifold air pressure (MAP) and the mass air flow (MAF) of the engine play an important role. More precisely, it has been shown that if the set-points for these two variables are chosen correctly, a precise tracking of these variables leads to an efficient combustion process that corresponds to a low level of emission [16][20]. The control inputs are the exhaust gas recirculation (EGR) and the variable geometry turbocharger (VGT) valves. It is shown hereafter that a simple low-dimensional parametrization of the control profile leads to a solution that is real-time implementable while explicitly addressing the constraints on both the control input and its derivative. Moreover, the resulting controller may work as a black box system, making the solution a priori compatible with any possible future improved model.

An identified model has been obtained [19] based on real world test bench[2]. Results

[2] BMW M47TUE diesel engine, at Johannes Kepler University Linz

showed that the MAF and the MAP are basically influenced by the control inputs EGR, VGT, and by two measured disturbances, namely fuel injection and speed engine. The identified model, sampled at 50 ms, shows the following structure:

$$x^+ = [A(u,w)]x + [B]u + [G]w$$
$$y = [C(u,w)]x$$

where $x \in \mathbb{R}^n$ is the state (n=8), $y \in \mathbb{R}^m$ is the vector of measured and regulated output (m=2), namely, the MAF and the MAP, $w \in \mathbb{R}^2$ is the measured disturbance vector (namely, the fuel injection and the engine speed) and $u \in \mathbb{R}^2$ is the control input representing the position (in %) of the EGR and VGT valves. The following constraints are imposed on the controlled inputs:

$$u_c + u \in [u_{min}, u_{max}]$$
$$\delta u \in [-\delta_{max}, +\delta_{max}]$$

where $\delta u = u(t_{j+1}) - u(t_j)$ and u_c is the central value around which the model is identified. The control problem is to design an output feedback that forces the regulated output y to approximately track some desired set-point $y_d \in \mathbb{R}^m$. Therefore, the controller needs the states that affect the evolution of the regulated output to be reconstructed. For this purpose, a Moving Horizon Observer (MHO) is designed [for more details, the reader can refer to [17]]. Having the state estimation $\hat{x}(t_j)$ at hand, the CPA consists basically in the computation of the steady state control u^* and the definition of a temporal parametrization that structurally meets the constraints. The steady state control u^* and the corresponding stationary state x^* can be calculated by solving a simple optimization problem. More precisely given the measured vector w and the desired value y_d, The steady state control is computed by solving the following two-dimensional optimization problem:

$$u^*(w, y_d) := arg \min_{u_d \in \mathbb{U}} \|y_c(u_d, w) - y_d\|^2 \quad ; \quad u_d \in [u_{min}, u_{max}] \tag{6}$$

$$y_c(u_d, w) = C(u_d, w)[\mathbb{I}_n - A(u_d, w)]^{-1} \cdot [B.u_d + G.w] \tag{7}$$

$$x^*(u^*, w) = [\mathbb{I}_n - A(u^*, w)]^{-1} \cdot [B.u^* + G.w] \tag{8}$$

Based on the steady state control $u^*(w, y_d)$, the following temporal parametrization can be defined:

$$u^{(i)}(p, \hat{x}(t_j)) = Sat_{u_{min}-u_c}^{u_{max}-u_c}\Big(u^* + \alpha_1(p).e^{-\lambda.i\cdot\tau} + \alpha_2(p).e^{-b\cdot\lambda.i\cdot\tau}\Big) \tag{9}$$

where the α_i's are solutions of the following p-dependent linear system of equations:

$$u^* + \alpha_1(p) + \alpha_2(p) = u(t_j) \tag{10}$$

$$(e^{-\lambda\cdot\tau} - 1) \cdot \alpha_1(p) + (e^{-b\cdot\lambda\cdot\tau} - 1) \cdot \alpha_2(p) = p\delta_{max} \quad ; \quad p \in [-1, +1]^2 \tag{11}$$

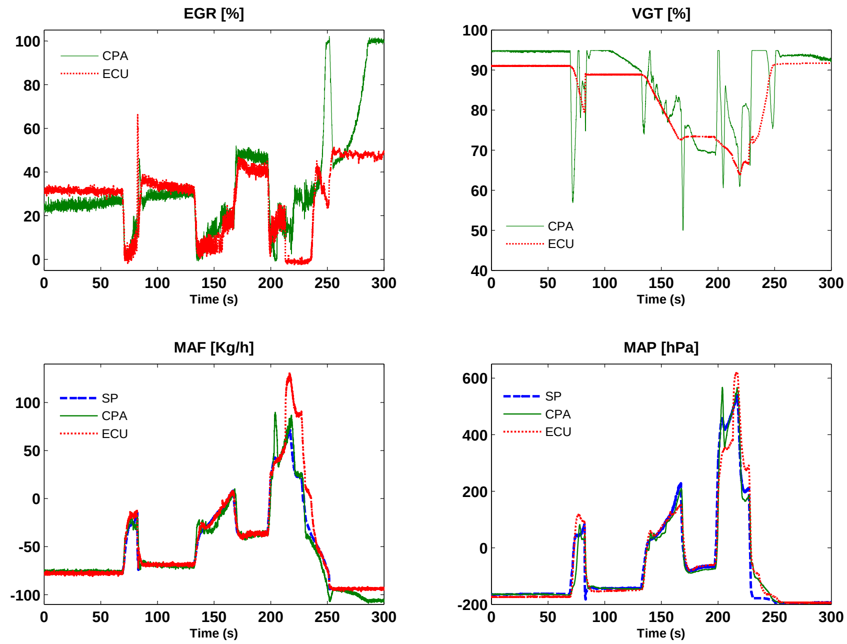

Fig. 1 Experimental results of the real-time parameterized NMPC under a part of the NEDC reference, using N_p=1.5s, λ=1, b=5 and 30 iterations. The values of MAP and MAF are relative ones. Except in the end, where model uncertainties are very high, the CPA provides a good tracking performance for MAF and MAP

where $\lambda > 0$, $b \in \mathbb{N}$ are fixed parameters. The two components of $p \in [-1,+1]^2$ are the only remaining degrees of freedom that have to be optimized on-line (together with the online computation of $u^*(w,y_d)$). Moreover, the continuity of the control sequence can be guaranteed in (10) and the constraints on the derivative are met in (11). Based on the above notation, the cost function used to compute the best control parameter p is defined as follows:

$$J(p,\hat{x}(t_j)) = \sum_{i=1}^{N} \|Y(i,\hat{x}(t_j),p) - Y^*(i,y(t_j),y_d)\|^2 + \rho \cdot \|X(N,\hat{x}(t_j),p) - x^*(u^*,w)\|$$

$$Y^*(i,y_d) = y_d + e^{-3\tau.i/t_r} \cdot [y(t_j) - y_d]$$

where $Y^*(i,y(t_j),y_d)$ is a filtered version for the set points, t_r the desired settling time of the closed loop and ρ a weighting term on the terminal state. For more details on the optimisation process and the time needed for its on-line solution, see [17]. Let us note however that given the small size of the optimization problems, several simple non-smooth optimization algorithms (Powell, simplex, etc.) have been tested without noticeable differences in the results.

Experimental validation on the real world Diesel engine is shown on Figure 1. The real time platform used is a 480MHz Autobox-dSPACE system. The routines were developed in C language using the Matlab environment and 50 *ms* as sampling period. A part of the New European Driving Cycle (NEDC) is used as validation scenario and results are compared to the performance obtained via the existing Engine Control Unit (ECU). One can note that during the time interval $[200-250]$ s, the NMPC controller outperforms the ECU while it gives roughly the same performance elsewhere. For completeness, note that an integrator was added in the control design in order to eliminate the offset error [17]. Recall that the proposed scheme can be easily used with more elaborated and fully nonlinear models without noticeable increase in complexity or computation time. Preliminary results in that direction are very promising and will be reported in future communications.

4 Example 2: Automated Manual Transmission control

Automated Manual Transmission (AMT) technology combines the fuel efficiency of manual transmission with the smooth operation of an automatic transmission. It operates similarly to a manual transmission except that it does not require direct clutch actuation or gear shifting by the driver. Transmission actuators are computer-controlled and embedded control strategies are in charge of ensuring smooth clutch engagement and gear shifting. AMT control has attracted considerable attention in the last recent years [14, 7, 13, 15, 9, 5] and a detailed state-of-the-art discussion is clearly beyond the scope of this contribution. However, it is relevant for the present contribution to mention that real-time implementation was a major issue in all the contributions that involved optimal control-like design. A detailed recent study, [15] concluded that due to its large computational cost, explicit MPC such as the one used in [7] is not suitable yet for this type of problems. The same statement applies to the constrained finite horizon LQ scheme proposed in [14] because of the classical parametrization being used. Finally, the NMPC clutch engagement strategy proposed in [9] involves an initial open-loop phase using look-up table since prediction horizon longer than 0.6 seconds would be incompatible with real-time requirements.

In what follows, it is shown how a parameterized approach enables a unified (start-up and gear shifting) and completely closed-loop real-time NMPC that explicitly handles the problem constraints to be obtained. However, because of the lack of space, only a sketch of the solution is proposed as the detailed description and results can be found in [5, 6]. In particular, the presentation concentrates on the start-up mode while the proposed solution [5, 6] covers all the gearing configurations. The system can be described by the following simplified model:

$$J_e\dot{\omega}_e = T_e - sign(\omega_{sl})\cdot T_c(x_c) \quad (12)$$
$$\big[J_c + J_e(i_g,i_d)\big]\dot{\omega}_c = sign(\omega_{sl})\cdot T_c(x_c) - g(\omega_c,\theta_{cw},\omega_w,i_g,i_d) \quad (13)$$
$$J_w\dot{\omega}_w = (i_g i_d)\cdot g(\omega_c,\theta_{cw},\omega_w,i_g,i_d) - T_L(\omega_w) \quad ; \quad \dot{\theta}_{cw} = \frac{\omega_c}{i_g i_d} - \omega_w \quad (14)$$

where the J's, T's, ω's and θ's represent inertias, torques, angular velocities and angles respectively. The indices e, c, m, t, w and L refer to engine, clutch, mainshaft, transmission, wheel and load respectively. i_g and i_d are the gear ratio and the differential ratio while J_{eq} is the equivalent inertia. Finally, $\omega_{sl} = \omega_e - \omega_c$ is the slip speed and $\theta_{cw} = \theta_c - \theta_w$. The control objective is to:
1) guarantee a smooth clutch engagement by forcing ω_{sl} to track a dynamically generated reference $\omega_{sl}^{ref}(\cdot)$ that reaches 0 after some transient time t_f. This duration t_f must faithfully reflect the actual driver torque demand expressed through the accelerator pedal position X_{pedal} (*transparency*).
2) regulate ω_e around some reference value $\omega_e^{ref} = \max\big\{\omega_e^0, \mathscr{T}^{-1}(T_e^d(X_{pedal},\omega_e))\big\}$ where ω_e^0 is the idle speed set-point, $\mathscr{T}(\omega_e)$ is the maximum torque at speed ω_e while T_e^d is the desired torque as interpreted from some static map given the pedal position X_{pedal} and the engine speed ω_e.

These control objectives have to be fulfilled while meeting saturation constraints on the control inputs ($T_e \in [T_e^{min}, T_e^{max}(\omega_e)]$, $T_c \in [T_c^{min}, T_c^{max}(\omega_e)]$) and their rates of change ($\dot{T}_e \in [\dot{T}_e^{min}, \dot{T}_e^{max}]$, $\dot{T}_c \in [\dot{T}_c^{min}, \dot{T}_c^{max}]$).

In order to design a real-time implementable MPC, the model (12)-(14) is simplified as follows:

$$J_e\dot{\omega}_e = u_1 - sign(\omega_{sl})\cdot u_2 + \delta_e \quad (15)$$
$$\big[J_c + J_e(i_g,i_d)\big]\dot{\omega}_c = sign(\omega_{sl})\cdot u_2 - \delta_c \quad (16)$$

where $u = \big(T_e^{sp}, T_c^{sp}\big)^T$ is the vector of set-points fed to the low level torque controllers while δ_e and δ_c gather all model mismatches and/or tracking errors including the unknown torque T_L. The MPC described hereafter uses estimated version $\hat{\delta}_e$ and $\hat{\delta}_c$ of δ_e and δ_c obtained through a Kalman-like observer using the measurement u, ω_e and ω_c.
Given a prediction horizon $N_p\cdot\tau$, the parameterized solution involves a scalar parameter p that is used to define a quadratic cost in the p.w.c control profile $\mathbf{u}$ according to

$$\Omega(\mathbf{u},p,\omega(k)) := \sum_{i=1}^{N_p}\left\|\begin{pmatrix}\omega_{sl}(k+i) - \omega_{sl}^{ref}(k+i,p)\\ \omega_e(k+i) - \omega_e^{ref}(k+i)\end{pmatrix}\right\|_Q \quad \text{where} \quad (17)$$
$$\omega_{sl}^{ref}(k+i,p) = \frac{1-i/p}{(1+\lambda\cdot i/p)^2}\omega_{sl}(k) \quad (18)$$

Referring to the notation of section 2, the following definitions are used:

$$J(p,\omega) = |p - t_f(X_{pedal})| \quad ; \quad \mathscr{U}_{pwc}(p,\omega) = arg\min_{\mathbf{u}} \Omega(\mathbf{u},p,\omega) \tag{19}$$

$$\Big\{C(p,\omega) \leq 0\Big\} \quad \Leftrightarrow \quad \Big\{\mathscr{U}_{pwc}(p,\omega) \quad \text{meets the constraints}\Big\} \tag{20}$$

where $t_f(X_{pedal})$ is the clutch engagement time associated to the pedal position X_{pedal} as computed from a look-up table while $\mathscr{U}_{pwc}(p,\omega)$ is the analytically given UNCONSTRAINED minimum of the quadratic cost (17). More precisely, p must be chosen as close as possible to t_f while resulting in an admissible control profile. It can be proved that this problem is feasible over the region of interest and can be solved by simple dichotomy. Figure 2 shows experimental results of a start-up ma-

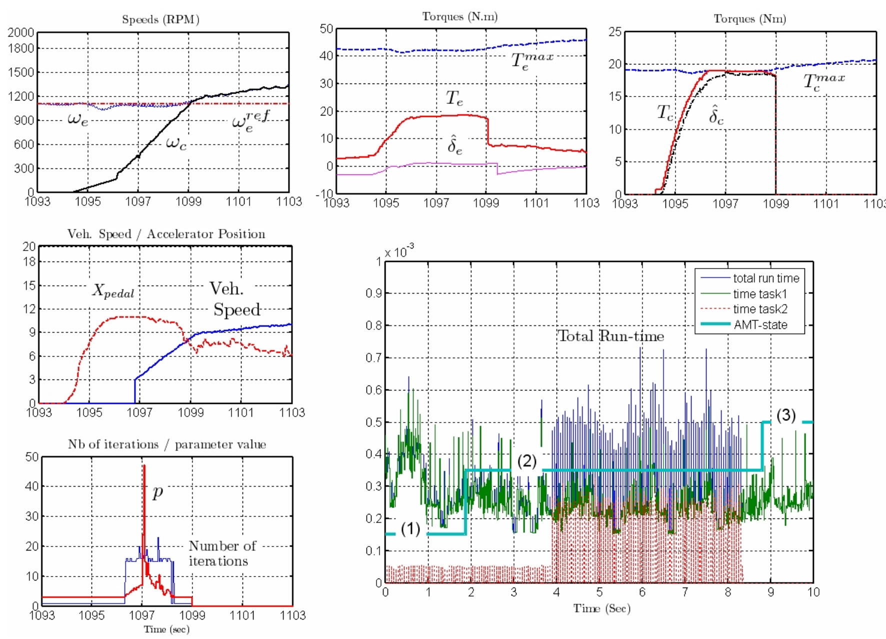

Fig. 2 Experimental validation of the real-time parameterized control strategy on the IFP-SMART car AMT. The central plot shows a typical evaluation of the tasks computation time . The MPC-related computation time never exceeds 0.35 *ms* that is reached during saturation phase where the number of iterations needed for the dichotomy is around 21 iterations. Note that during these period, the scalar parameter increases drastically in order to meet the actuators constraints.

noeuver using the parameterized MPC. Note the saturation on the applied torques as well as the evolution of the parameter p that reached 47 during the saturation phase. The central plot shows a typical evaluation of the processor computational load. The software has been run in a multi-task configuration including two tasks: a secondary task (task2) corresponding to the MPC algorithm, computed every 50*ms* and a main task (task1), including the rest of the powertrain control modules, computed every 1*ms*. The MPC strategy takes approximately 0.05 ms when only one iteration is needed. Whereas during constraint saturation this time increases to a mean of approximately 0.28 *ms* (≈ 15 iterations) with a maximum of 0.35 *ms* (≈ 21 iterations). The control software is written in MATLAB/Simulink and run in real-time on a xPC Target environment hosted on a micro-PC with a 1GHz Pentium III and 256 Mb of RAM of which only 0.3 Mb are used by the engine control software.

5 Conclusion

In this paper, the parametric approach to NMPC implementation is described and two automotive control problems are used to illustrate its efficiency. The main goal of this paper is to underline the fact that generic formulations are rarely compatible with available real-time and embedded computational facilities. However, dedicated and even oversimplified settings may lead to remarkably nice results thanks to the receding-horizon principle's efficiency in recovering closed-loop optimality.

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