NMPC for a Diesel Engine Formulation and Experimental Validation

André Murilo

Supervisor: Mazen Alamir

GIPSA-lab / SYSCO-team
In collaboration with University of Linz, Austria

Email: andre.murilo@gipsa-lab.fr
www.lag.ensieg.inpg.fr/murilo

Outline

Diesel Engine

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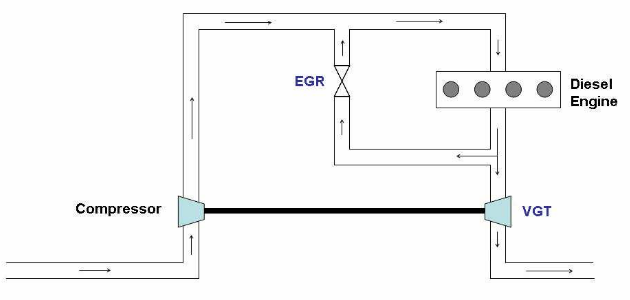
- Advantages
    - Reduced fuel consumption
    - Important torque at low speed

Diesel Engine

- Advantages
  - Reduced fuel consumption
  - Important torque at low speed
- Drawback
  - Emissions of oxides of nitrogen (NOx) and particulate matter (PM)

Diesel Engine Air-Path



The inputs

- Exhaust Gaz Recirculation (EGR)
- Variable Geometry Turbocharger (VGT)

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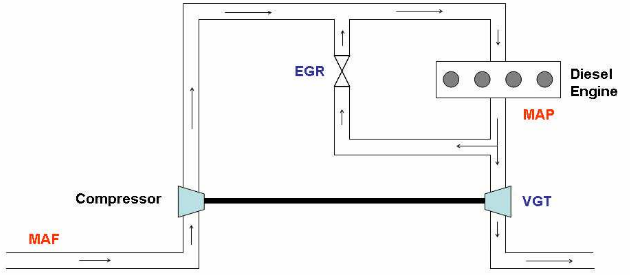
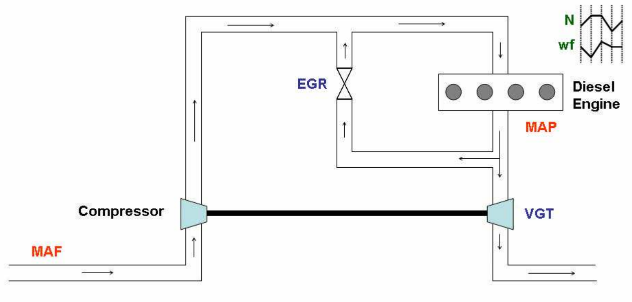
Diesel Engine Air-Path



Control of emission needs to track the following outputs

- Manifold Air Pressure (MAP)
- Mass Air Flow (MAF)

Diesel Engine Air-Path



The measured disturbances

- Engine Speed (N)
- Fuel Injection (wf)

System Modeling

Model 1

$$
\begin{aligned}
x_1^+ &= [A(y)]x_1 + B_1 u + G_1 w \\
y_1 &= [C(y)]x_1
\end{aligned}
$$

- $x_1 \in \mathbb{R}^{n=13}$
- Sampling Time $\tau_s = 10\ ms$

System Modeling

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Model 2

$$\begin{aligned} x_2^+ &= [A(u,w)]x_2 + B_2 u + G_2 w \\ y_2 &= [C(u,w)]x_2 \end{aligned}$$

- $x_2 \in \mathbb{R}^{n=8}$
- Sampling Time $\tau_s = 50\ ms$

System Modeling

Model 1

$$x_1^+ = [A(y)]x_1 + B_1 u + G_1 w$$
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Outputs :

- $y := (MAP, MAF)^T \in \mathbb{R}^2$

Inputs :

- $u := (EGR, VGT)^T \in \mathbb{R}^2$
- $w := (N, wf)^T \in \mathbb{R}^2$

Constraints :

- $u \in [u^{min}, u^{max}]$ (componentwise)
- $|\delta u| \in [-\delta^{max}, +\delta^{max}]$

Moving Horizon Observer

- Based on a moving and fixed-size window *No* of past measurements

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- Application to nonlinear systems

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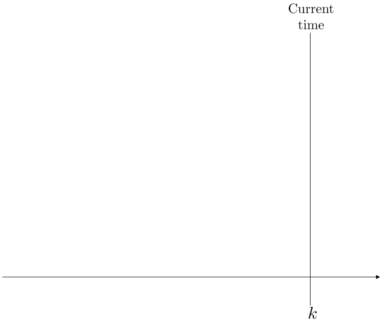
- Application to nonlinear systems
- MHO uses the maximum of information on the part of the state that affects the measured output

Moving Horizon Observer



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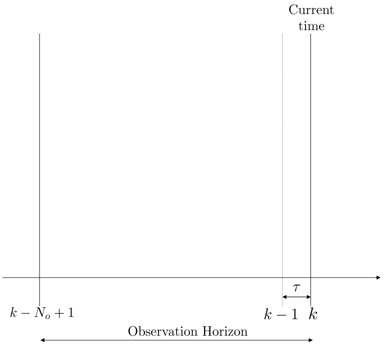

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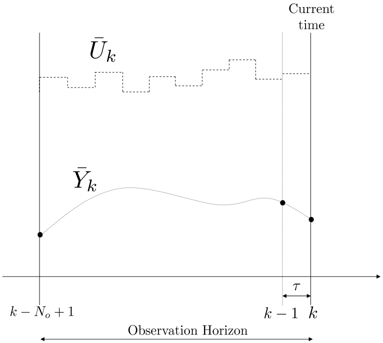

Past inputs and outputs

$$\bar{Y}_k := \begin{pmatrix} y_{k-N_o+1} \\ \vdots \\ y_k \end{pmatrix} \quad , \quad \bar{U}_k := \begin{pmatrix} w_{k-N_o+1} \\ u_{k-N_o+1} \\ \vdots \\ w_{k-1} \\ u_{k-1} \end{pmatrix}$$

System of equations depending on U_k

$$\begin{aligned} x_k &= \left[\Phi(\bar{U}_k)\right] \cdot x^{(-)} + \left[\Psi(\bar{U}_k)\right] \cdot \bar{U}_k \\ \bar{Y}_k &= \left[\Omega(\bar{U}_k)\right] \cdot x^{(-)} + \left[\Gamma(\bar{U}_k)\right] \cdot \bar{U}_k \end{aligned}$$

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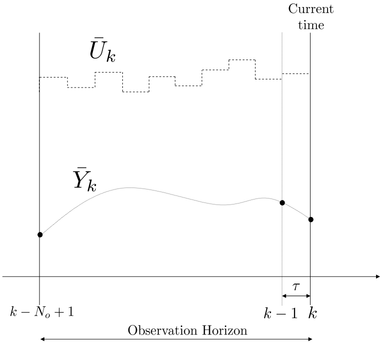
Moving Horizon Observer



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Condition at $k-1|k$

$$\begin{aligned} A(U_{k-1}) \cdot \hat{x}_{k-1} + B_1(U_{k-1}) \cdot u_{k-1} &= \left[\Phi(\bar{U}_k)\right] \cdot \hat{x}^{(-)} + \left[\Psi(\bar{U}_k)\right] \cdot \bar{U}_k \\ \bar{Y}_k &= \left[\Omega(\bar{U}_k)\right] \cdot \hat{x}^{(-)} + \left[\Gamma(\bar{U}_k)\right] \cdot \bar{U}_k \end{aligned}$$

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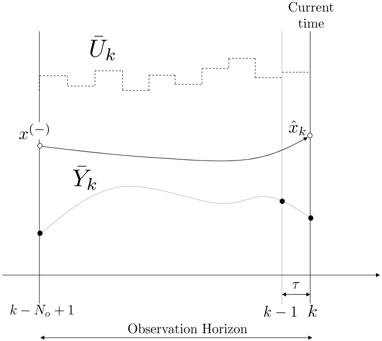

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$$A(U_{k-1}) \cdot \hat{x}_{k-1} + B_1(U_{k-1}) \cdot u_{k-1} - \left[\Psi(\bar{U}_k)\right] \cdot \bar{U}_k = \left[\Phi(\bar{U}_k)\right] \cdot \hat{x}^{(-)} \quad (1)$$

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$$\hat{x}_k = \left[\Phi(\bar{U}_k)\right]\cdot\xi_{opt}(\bar{U}_k,\bar{Y}_k,\hat{x}_{k-1}) + \left[\Psi(\bar{U}_k)\right]\cdot\bar{U}_k$$

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Application to the Diesel Engine

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NMPC Scheme

- Steady control u^*
- Define a temporal parametrization involving u^*

Computation of the steady control $u^*(y_d, w, u_d)$

Given the desired output y_d, the measured disturbance w and an initial guess for u_d, a candidate output y_c can be written as follows

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

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The steady control u^* is obtained by minimizing the following cost function J_s :

$$J_s(u_d) := \gamma \left\|y_c(u_d, w) - y_d\right\|^2$$

under the constraints :

$$u_d \in [u_{min}, u_{max}]$$

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And the steady state x^* can be obtained

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

Parametrization of the control profile

Given the desired output y_d, the measured disturbance w and the steady control $u^*(y_d, w, u_d)$, the piece-wise constant control $\mathbf{u}$ is defined by :

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where λ and q are the tunning parameters for the exponential modes

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1. Continuity of the control $(t = 0)$

   $u^* + \alpha_1 + \alpha_2 = u_k$

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Moreover, α_1 and α_2 must satisfy the following set of constraints :

1. Continuity of the control $(t = 0)$

   $u^* + \alpha_1 + \alpha_2 = u_k$

2. Parametrization of the derivative $(t = \tau)$

   $(e^{-\lambda\tau} - 1) \cdot \alpha_1 + (e^{-q\lambda\tau} - 1) \cdot \alpha_2 = p\delta_{max}$ where $p \in [-1, 1]^2$

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$$\begin{pmatrix} \alpha_1(p) \\ \alpha_2(p) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ e^{-\lambda\tau} - 1 & e^{-q\lambda\tau} - 1 \end{pmatrix}^{-1} \begin{pmatrix} u_k - u^*(y_d, w, u_d) \\ p\delta_{max} \end{pmatrix}$$

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Parametrization of the control profile

The n-dimentional exponential parametrization

$$\mathbf{u}(t) = Sat_{u_{min}}^{u_{max}}\left(u^*(y_d, w) + \alpha_1 e^{-\lambda t} + \alpha_2 e^{-q\lambda t} + \alpha_3 e^{-c_3 t} + \ldots + \alpha_n e^{-c_n t}\right)$$

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gives the following extended system of equations

$$\begin{pmatrix} \alpha_1(p, \alpha_3, \ldots, \alpha_n) \\ \alpha_2(p, \alpha_3, \ldots, \alpha_n) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ e^{-\lambda\tau} - 1 & e^{-q\lambda\tau} - 1 \end{pmatrix}^{-1} \begin{pmatrix} u_k - u^*(y_d, w, u_d) - \alpha_3 - \ldots - \alpha_n \\ p\delta_{max} - \alpha_3(e^{-c_3\tau} - 1) - \ldots - \alpha_n(e^{-c_n\tau} - 1) \end{pmatrix}$$

where

- $\alpha_3, \ldots, \alpha_n$ are the extra degree of freedom
- $c_3, \ldots, c_n$ are the respective exponential coefficients

Definition of the cost function

Given the desired output y_d, the measured disturbance w, the initial value of u_d and the estimated value of the state $\hat{x}^p_{k+1}$ at the next decision instant $k+1$, the cost function $J(p)$ can be defined as follows :

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$$J(p) := \sum_{i=1}^{N_p}\left[\left\|Y(i,p,\hat{x}^p_{k+1}) - Y^f(i,y_d,w)\right\|^2\right] + \rho_x\left\|X(N_p,p,\hat{x}^p_{k+1}) - x^*(y_d,w,u_d)\right\|^2$$

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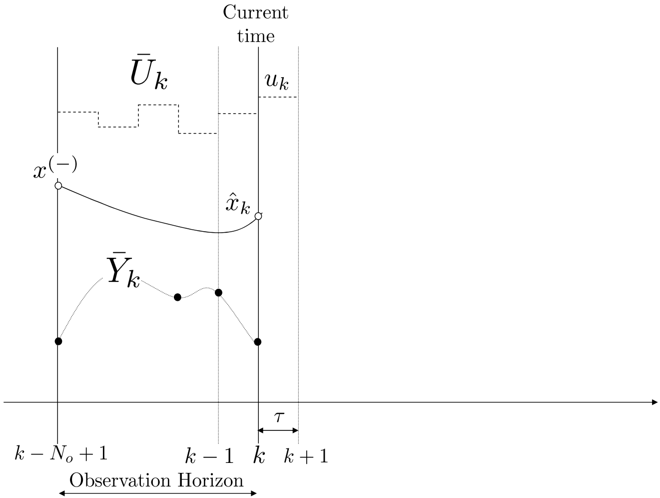
where :

- N_p is the prediction horizon
- ρ_x is the weighting term on the state
- $Y^f(i,y_d,w) := y_d + e^{-3\tau \cdot i/t_r} \cdot \left[y_k - y_d \right]$ is the filtered set-points
- $X(\cdot,p,\hat{x}_{k+1}^p)$ is the predicted state trajectory
- $Y(\cdot,p,\hat{x}_{k+1}^p)$ is the predicted output trajectory

To Summarize



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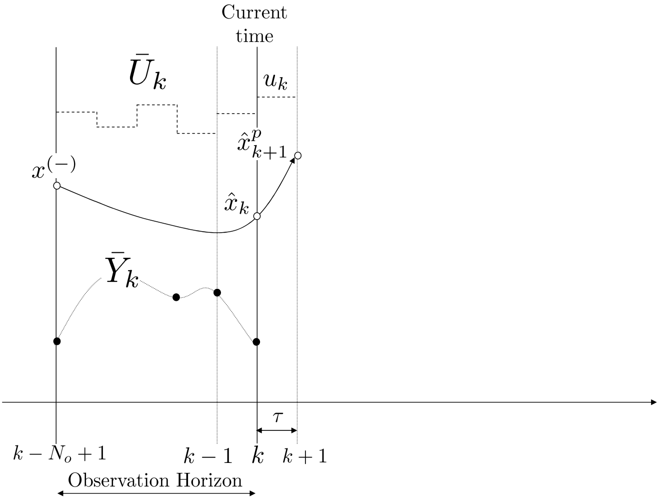

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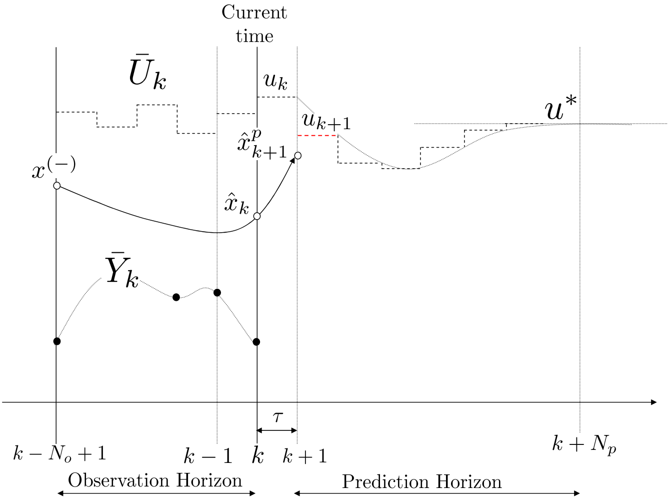

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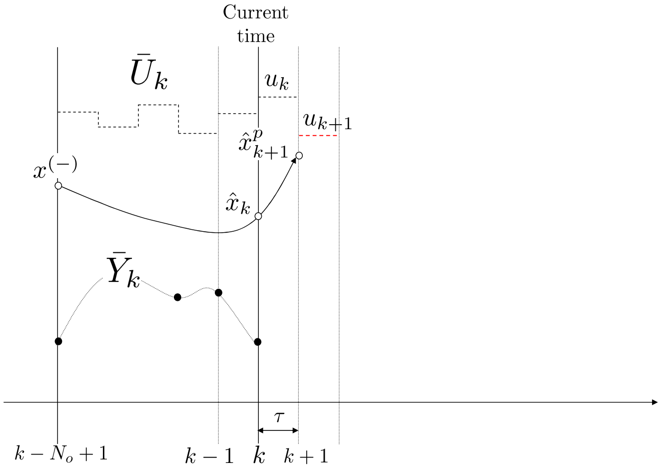
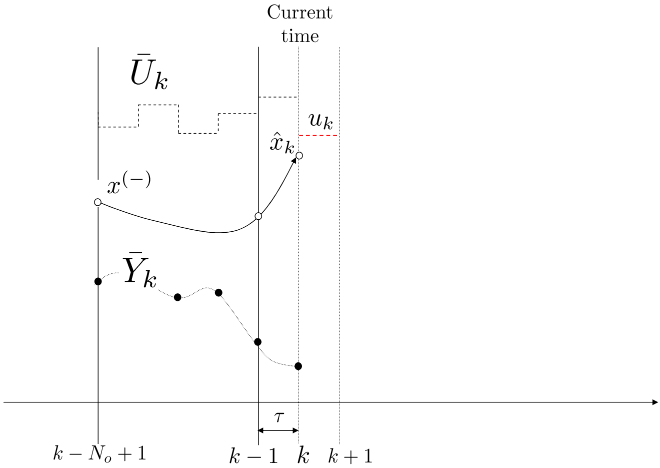
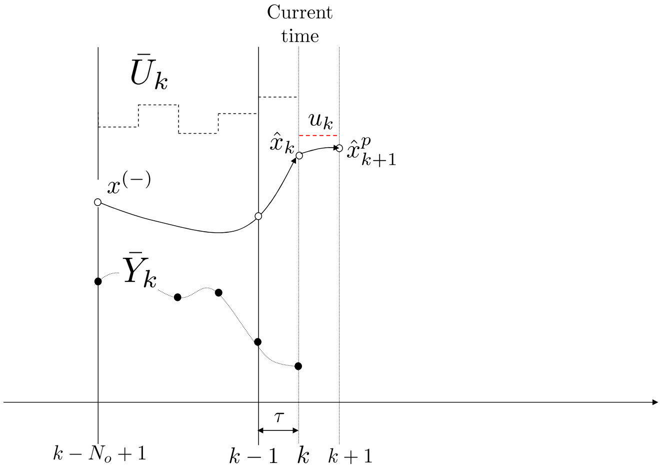


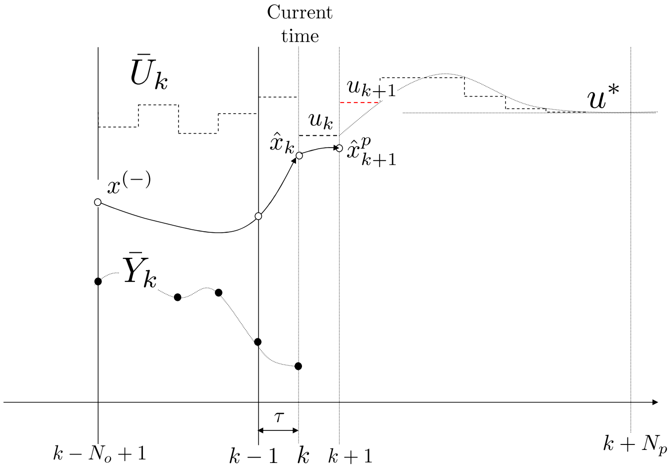
To Summarize



To Summarize

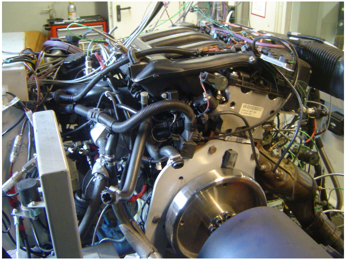


To Summarize



Experimental Results

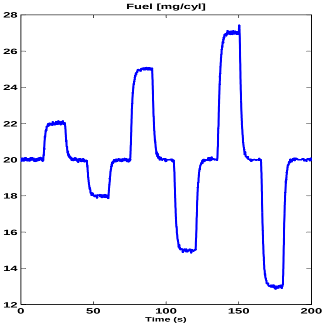
- Testbench at the University of Linz, Austria
- BMW M47D diesel engine
- ECU (Engine Control Unit) : Bosch
- Dynamic NOx measurements, response time : 4ms
- Partial flow opacimeter, response time : 0.1s
- PUMA (Prüfstands - Und Messtechnik - Automatisierung), Analog inputs 100 Hz and Speed/torque control 3000 Hz
- dSPACE Autobox
- Routine developed in C for Matlab S-functions

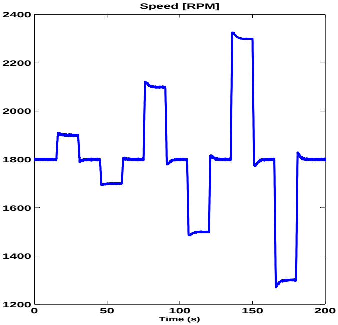


Experimental Results

Part I

- Generation of set points from a step sequence of speed N and fuel injection wf.

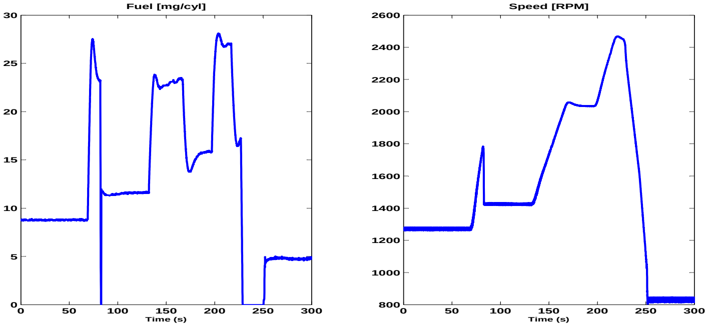




Experimental Results

Part II

- Generation of set points of *N* and *wf* from the PUMA system, with respect to the NECS (New European Driving Cycle)

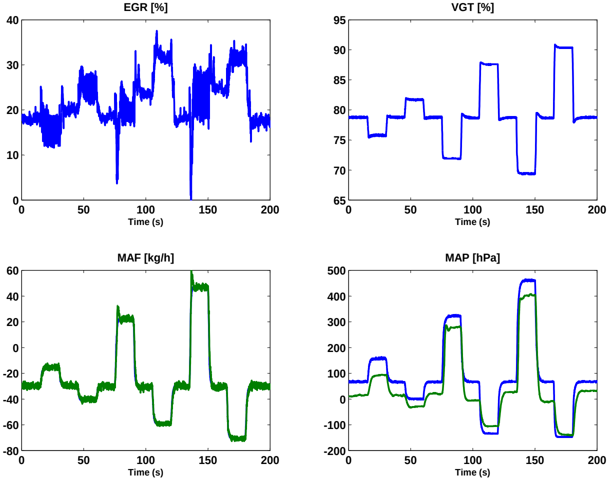


Experimental Results

Initial Configuration

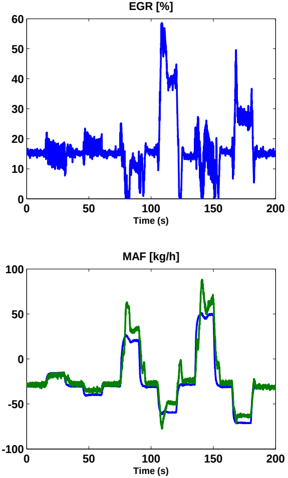
- Sampling Time τ=50 ms
- Prediction Horizon N_p=30 steps
- Observation Horizon N_o=10 steps
- Number of iterations $iter$=30
- Exponential mode λ=1
- Exponential mode q=5
- Weighting term ρ_x=1e-4
- Saturation on the inputs δu=[1 ;1]

Experimental Results - Part I - ECU



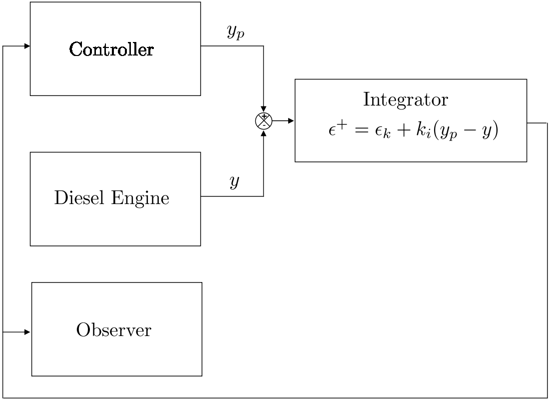
Feed-forward controller

Experimental Results - Part I - NMPC

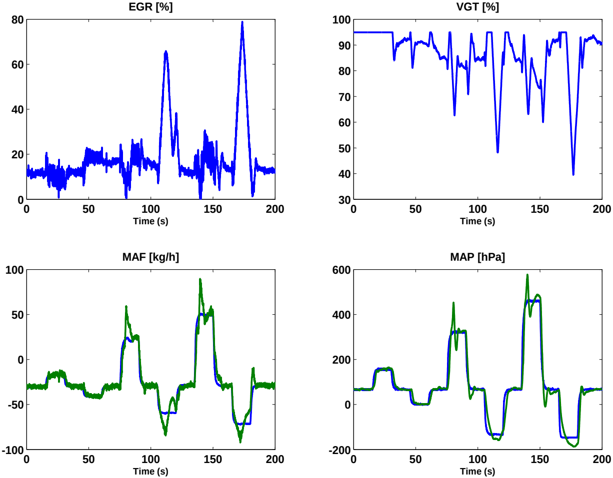


No offset tracking

Experimental Results - Part I - NMPC

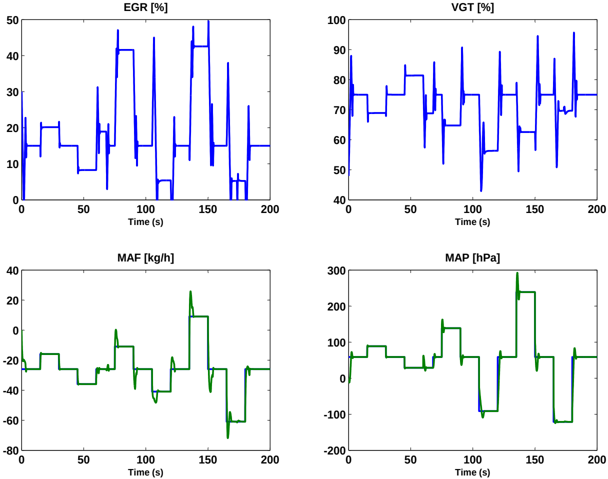


Experimental Results - Part I - NMPC



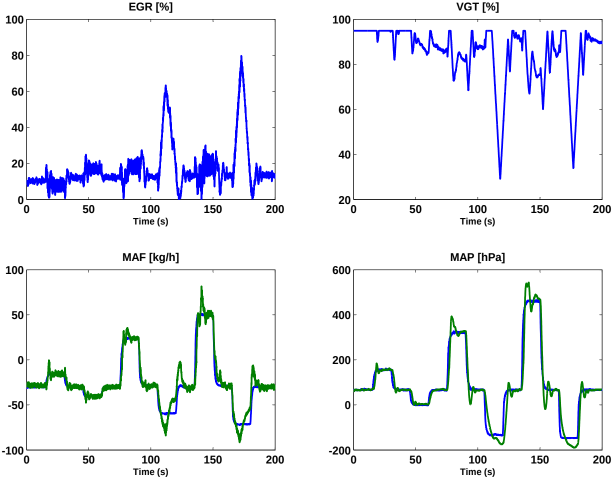
N_p=30 ; λ=1 ; q=5 ; ρ_x=1e-4 ; δ u=[1 ;1]

Simulation Results - Part I - NMPC



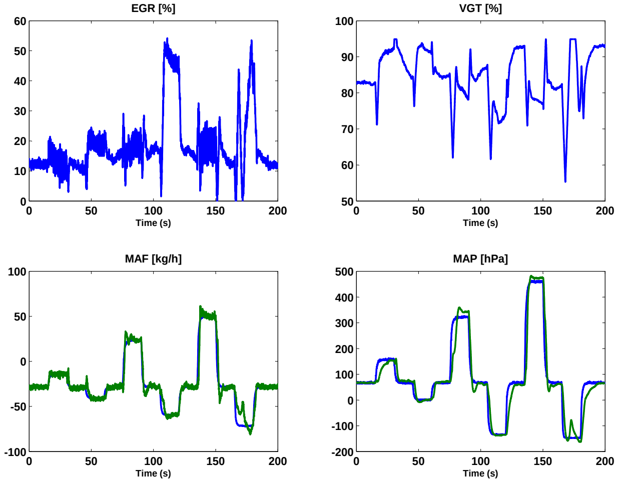
N_p=30 ; λ=1 ; q=5 ; ρ_x=1e-4 ; δ u=[1 ;1]

Experimental Results - Part I - NMPC



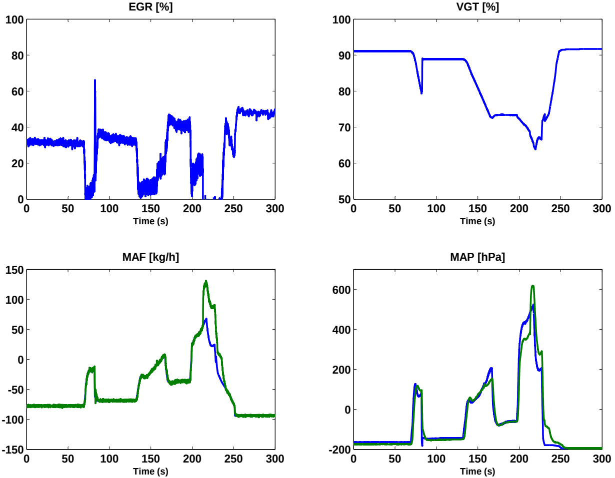
N_p=30 ; λ=1 ; q=5 ; ρ_x=1e-4 ; $\delta u = [0.5; 0.5]$

Experimental Results - Part I - NMPC



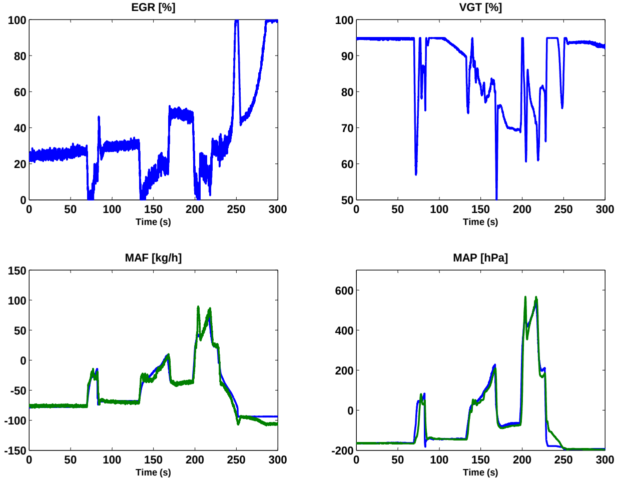
N_p=30 ; λ=1 ; q=5 ; $\rho_x = 1e4$; $\delta u = [1; 1]$

Experimental Results - Part II - ECU



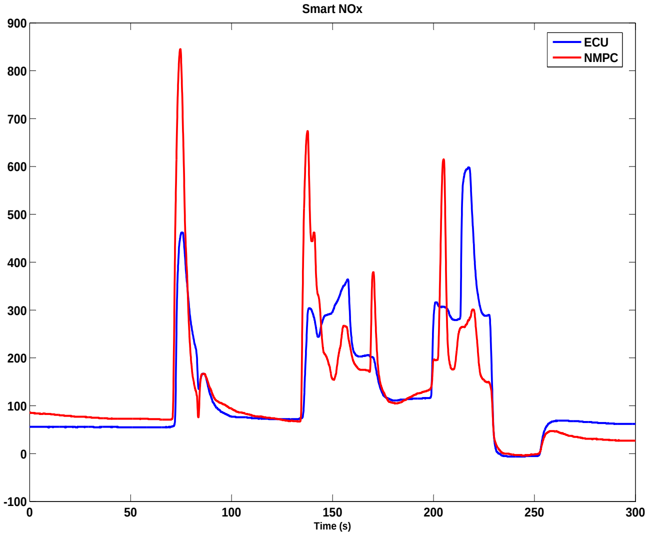
Feed-Foward

Experimental Results - Part II - NMPC



N_p=30 ; λ=1 ; q=5 ; $\rho_x = 1e - 4$; $\delta u = [1; 1]$

Experimental Results - Part II



Conclusion

- Low-dimensional parameterized NMPC scheme for the Diesel engine
- NMPC structure can be used for a more general class of nonlinear systems
- Good tracking performance for the step sequence and real-world simulation
- Real time implementable

Future Works

- Robust to fast/important set points variations
- Improvements on the steady state optimization problem
- Try better models