

# Optimizacija parametara modelskog prediktivnog upravljanja pomoću genetskog algoritma

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- Parametri algoritma i princip rada

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# Primjena genetskog algoritma na MPC

Objekt upravljanja

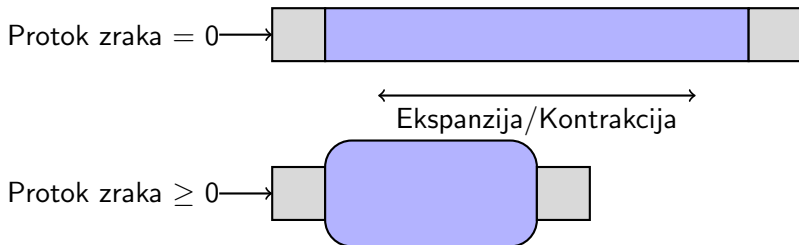


Figure: Princip rada pneumatskog aktuatora

# Primjena genetskog algoritma na MPC

Objekt upravljanja

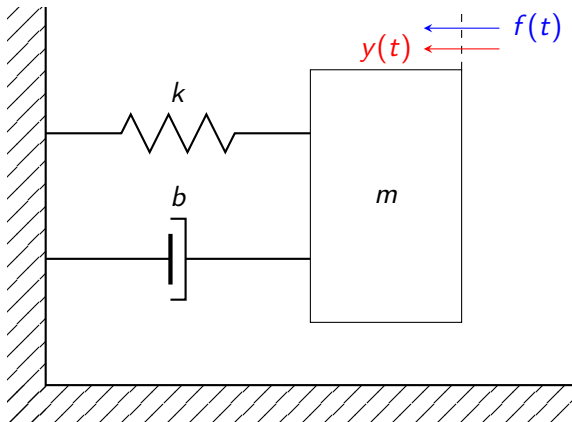


Figure: Shema sustava masa-opruga-prigušnica

# Primjena genetskog algoritma na MPC

## Objekt upravljanja

$$f(t) - m\ddot{y}(t) - b\dot{y}(t) - ky(t) = 0, \quad (1)$$

$$x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} y(t) \\ \dot{y}(t) \end{bmatrix} \quad (2)$$

$$\dot{x}_1(t) = x_2(t) \quad (3)$$

$$\dot{x}_2(t) = \frac{1}{m}f(t) - \frac{b}{m}x_2(t) - \frac{k}{m}x_1(t) \quad (4)$$

$$\dot{q}(t) = -\frac{1}{\tau}q(t) + \frac{K}{\tau}u(t) \quad (5)$$

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{q}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{k}{m} & -\frac{b}{m} & \frac{\gamma A}{m} \\ 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ q(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{K}{\tau} \end{bmatrix} u(t)$$

# Primjena genetskog algoritma na MPC

## Formiranje *fitness* funkcije

- argumenti  $\longrightarrow p, Q_{11}$
- cilj  $\longrightarrow$  optimalni omjer
- funkcija  $\longrightarrow f(p, Q_{11})$
- formiranje trodimenzionalnog prikaza *fitness* funkcije i pronalazak minimuma

# Primjena genetskog algoritma na MPC

Analiza parametara odziva pneumatskog aktuatora

- greška u stacionarnom stanju  $\varepsilon$ , vrijeme porasta  $t_r$

odziv\_MPC\_lose-eps-converted-to.pdf

# Implementation on a linear pneumatic muscle

## Problems and issues

- 3 state variables
- steady-state error - unable to compare with LQR and assess the validity
- the error dependent on  $\mathbf{Q}$  matrix and  $p$
- approx. linear error ratio with respect to  $p$  changes
- nonlinear error ratio with respect to  $\mathbf{Q}$  changes (unable to even measure)



# Implementation on a linear pneumatic muscle

## Simulation results

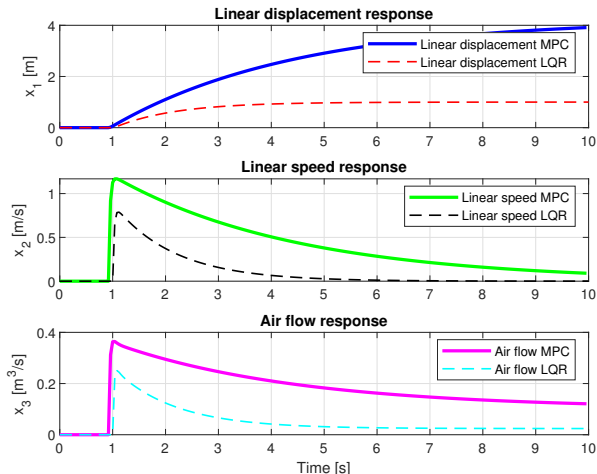


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 10$ ,  $m = 3$

# Implementation on a linear pneumatic muscle

## Simulation results

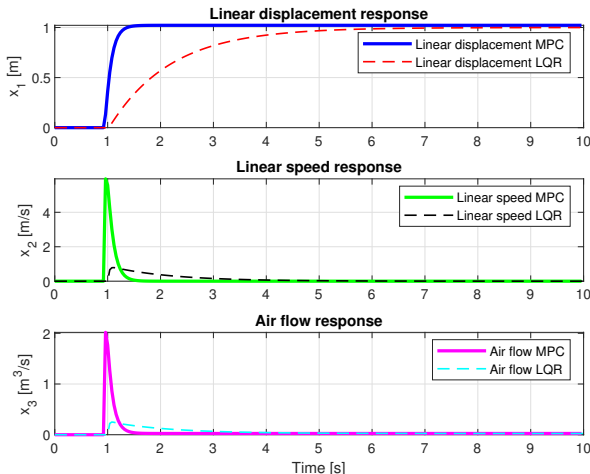


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 100$ ,  $p = 10$ ,  $m = 3$

# Implementation on a linear pneumatic muscle

## Simulation results

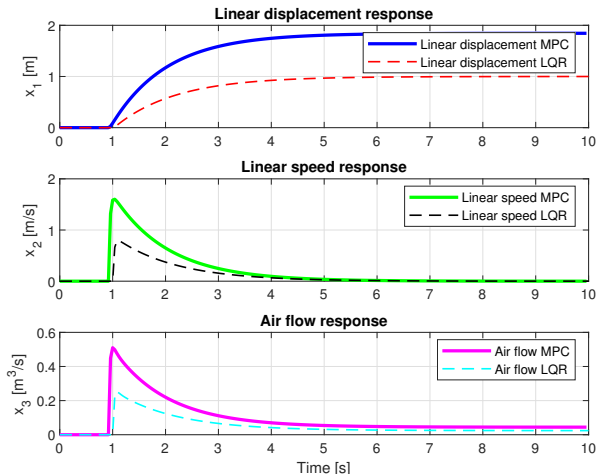


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 40$ ,  $m = 3$

# Implementation on a linear pneumatic muscle

## Further analysis

- verify and adjust system parameters
- study interactions between changes in  $Q$ ,  $p$ ,  $m$ , and  $T_s$
- deep analysis of the code and MPC loop with regard to literature and papers

# Implementation on a linear pneumatic muscle

## Corrections

- continuous LQR  $\rightarrow$  discrete LQR
- elimination of the discretization error
- corrections were insignificant

```
1 Ksystem = dlqr(Ad, Bd, Q, R);           %dlqr instead of lqr
```

# Model predictive control

## Corrections

- state-space model correction
- missing coupling term between the airflow state ( $x_3$ ) and the force ( $f$ )
- the force depends on the air pressure, affected by the airflow
- **$f$  shouldn't be treated as an independent input**

$$\dot{x}_2(t) = \frac{1}{m}f(t) - \frac{b}{m}x_2(t) - \frac{k}{m}x_1(t) \quad (6)$$

$$\dot{x}_2(t) = \frac{\gamma A}{m}x_3(t) - \frac{b}{m}x_2(t) - \frac{k}{m}x_1(t) \quad (7)$$

- $\gamma$  is a proportionality constant of the muscle, linking the airflow with the air pressure ( $P = \gamma x_3$ )
- $A$  is effective cross-sectional area of the muscle

# Model predictive control

## Corrections

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{q}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{k}{m} & -\frac{b}{m} & 0 \\ 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ q(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \\ \frac{k}{\tau} \end{bmatrix} \begin{bmatrix} 0 \\ f(t) \\ u(t) \end{bmatrix}$$

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{q}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{k}{m} & -\frac{b}{m} & \frac{\gamma A}{m} \\ 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ q(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{k}{\tau} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ u(t) \end{bmatrix}$$

# Model predictive control

## Corrections

- 1 input  $\rightarrow$  voltage applied to the valve
- insignificant corrections in responses

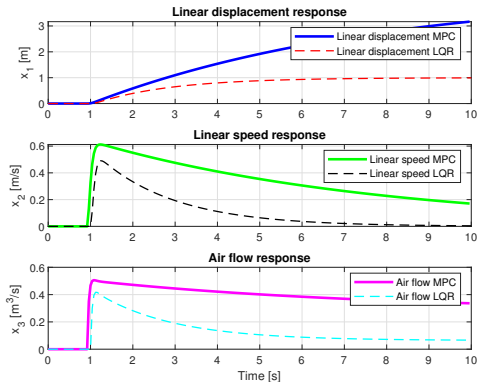


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 10$ ,  $m = 3$



# Model predictive control

## Corrections

- **natural responses match at  $\approx p = 40$**
- **forced responses mismatch**
- if we define the steady-state MPC error as

$$SS_{MPC} = e \cdot SS_{LQR} \quad (8)$$

and  $SS_{LQR} = 0$ , then  $SS_{MPC}$  must also be equal to 0

# Model predictive control

## Corrections

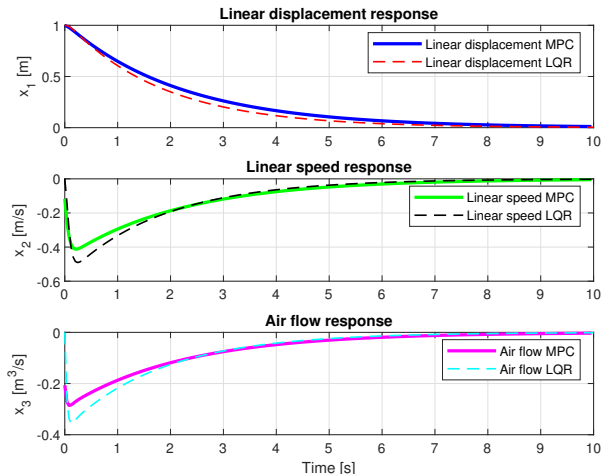


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 40$ ,  $m = 3$

# Model predictive control

## Corrections

- valid constraints

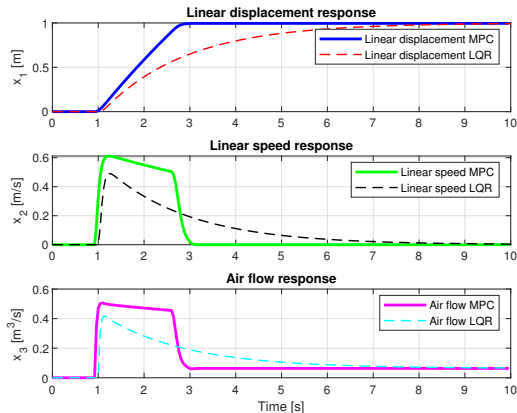


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 10$ ,  $m = 3$

# Model predictive control

## Corrections

- MPC with  $p \rightarrow \infty$  approaches LQR

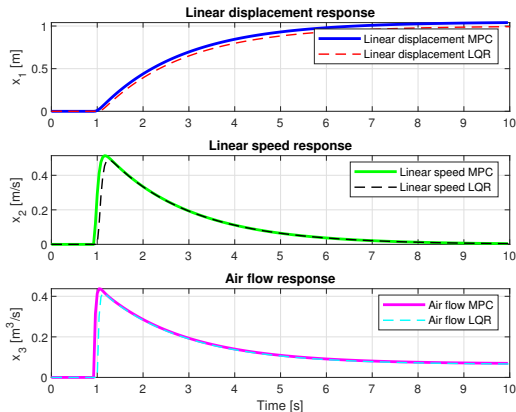


Figure:  $Q_{LQR} = 1$ ,  $Q_{MPC} = 1$ ,  $p = 400$ ,  $m = 400$

**Thank you! Questions?**