Machine Learning Based Control Algorithm for Active Vibration Suppression of a Mechanical Flexure Hinge

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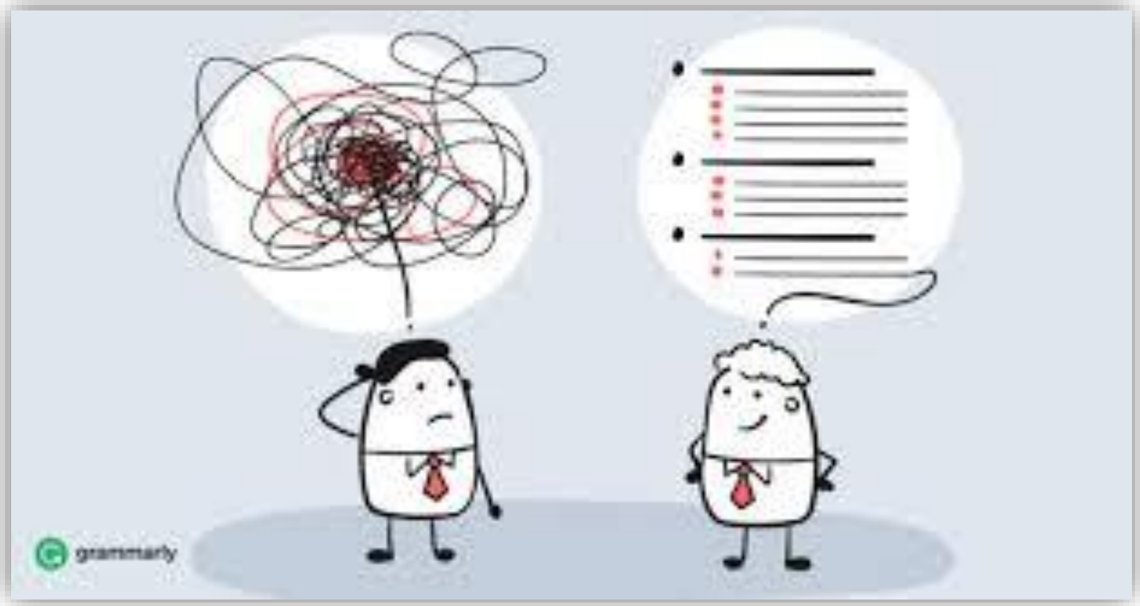
Outline

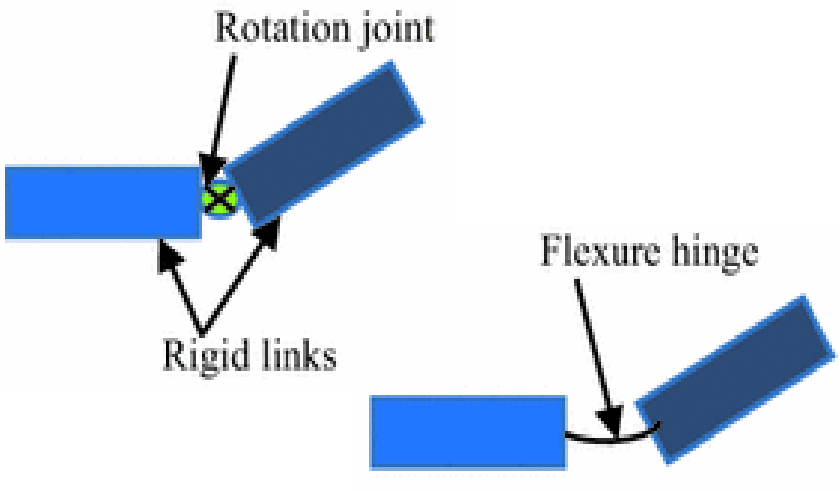
- Background
- Our goal
- Results
- Conclusion
- Time for questions



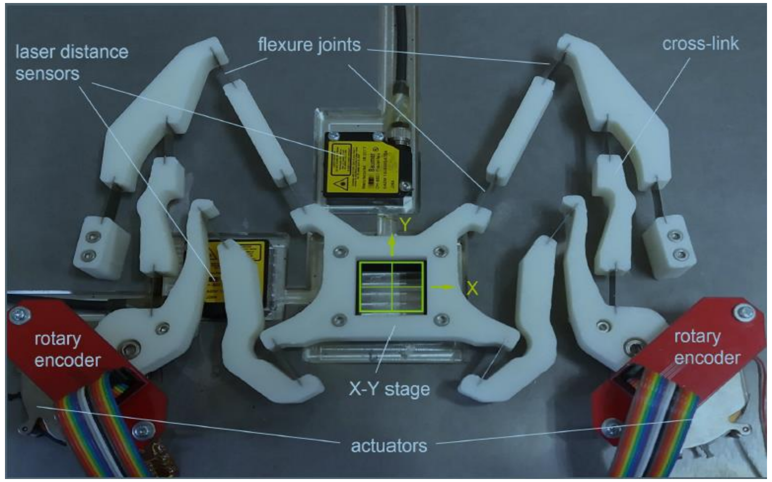
Background – Applications of flexible structure (examples)

Aircraft

Satellite



Manipulator mechanism



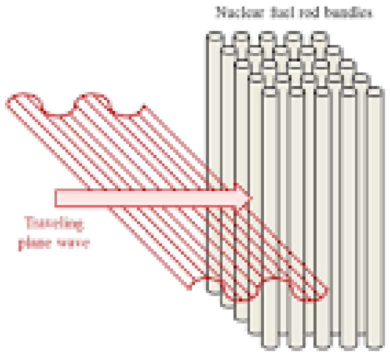
X-Y micro-positioning stage

Background – Applications and problems

- Flexible mechanical structures form vital components in a wide range of engineering systems.
- Vibration suppression of a flexible mechanical structures is relevant to the design and operation of systems.
- The mechanical vibration may be a cause of various types of problems, such as
  - System dynamic instability
  - Fatigue damage
  - Fretting fatigue

cylindrical vessel

Submarine, missiles and rockets



Flexural vibration of nuclear fuel rod bundles

Background – Research issues

- Active vibration control of flexible structures has become a popular research interest.
- In many vibration control problems, the goal is to suppress the effect of external disturbances under unknown parameters and time-variant parameters while keeping the structure in its equilibrium state.
- The optimal control method is based on the dynamic model, in linear cases also achieves the optimal control function.
- A machine learning method can replace optimal control by finding a solution close to optimal for cases where the dynamic model is unknown.

Our goal

The aim of this study is to investigate a machine learning control method for active vibration suppression of a mechanical flexure hinge.

System Architecture – main components

Main components

Flexible hinge

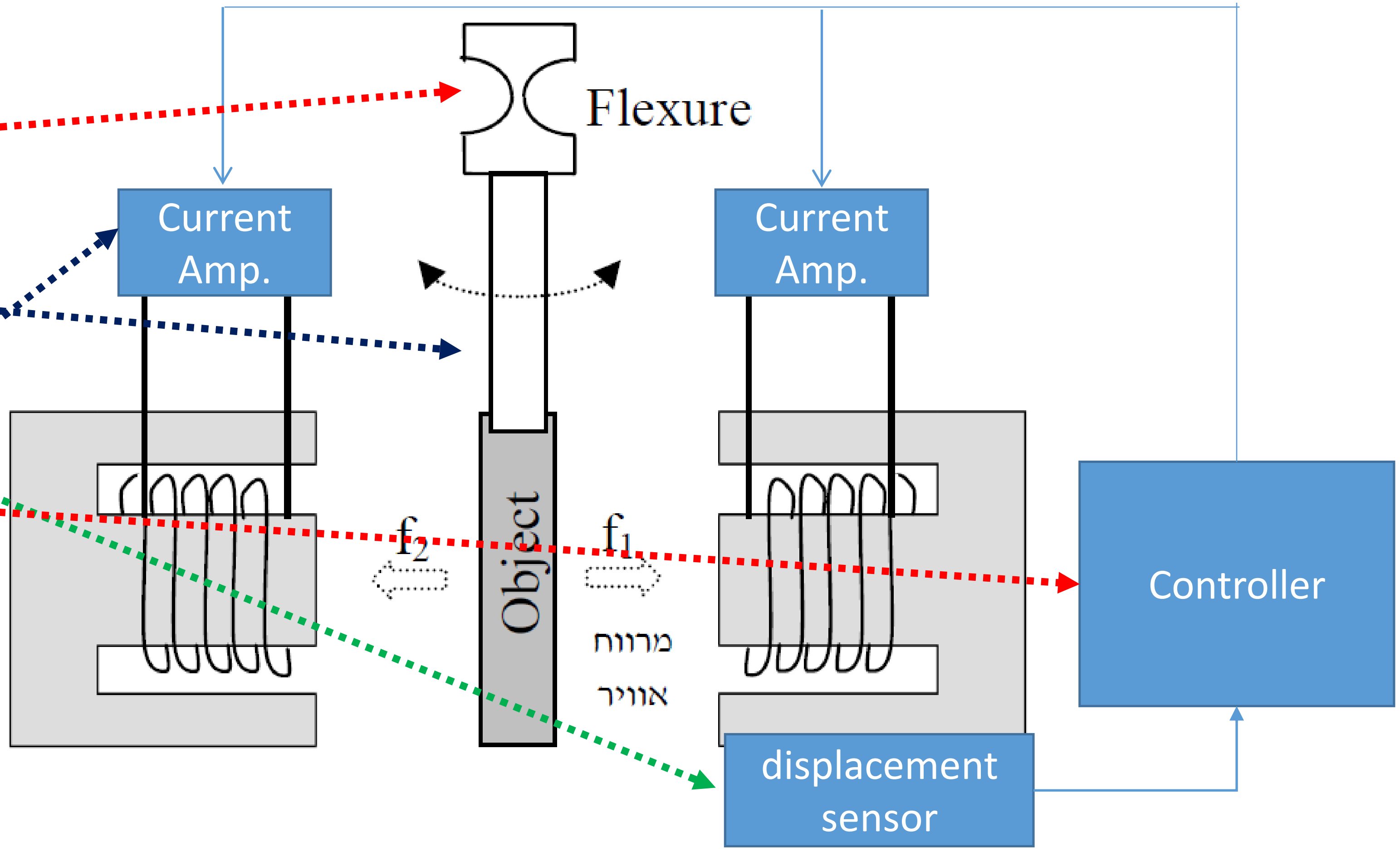
Rigid shaft

Displacement sensor

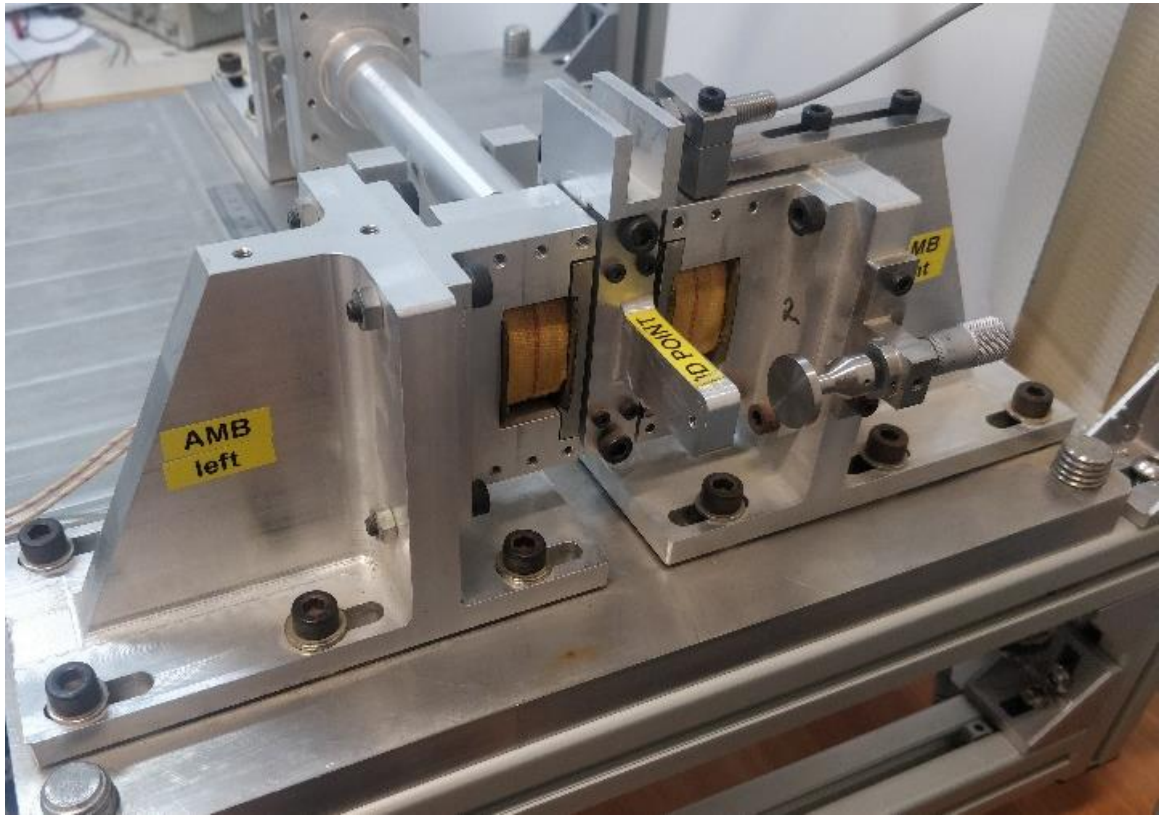
Controller

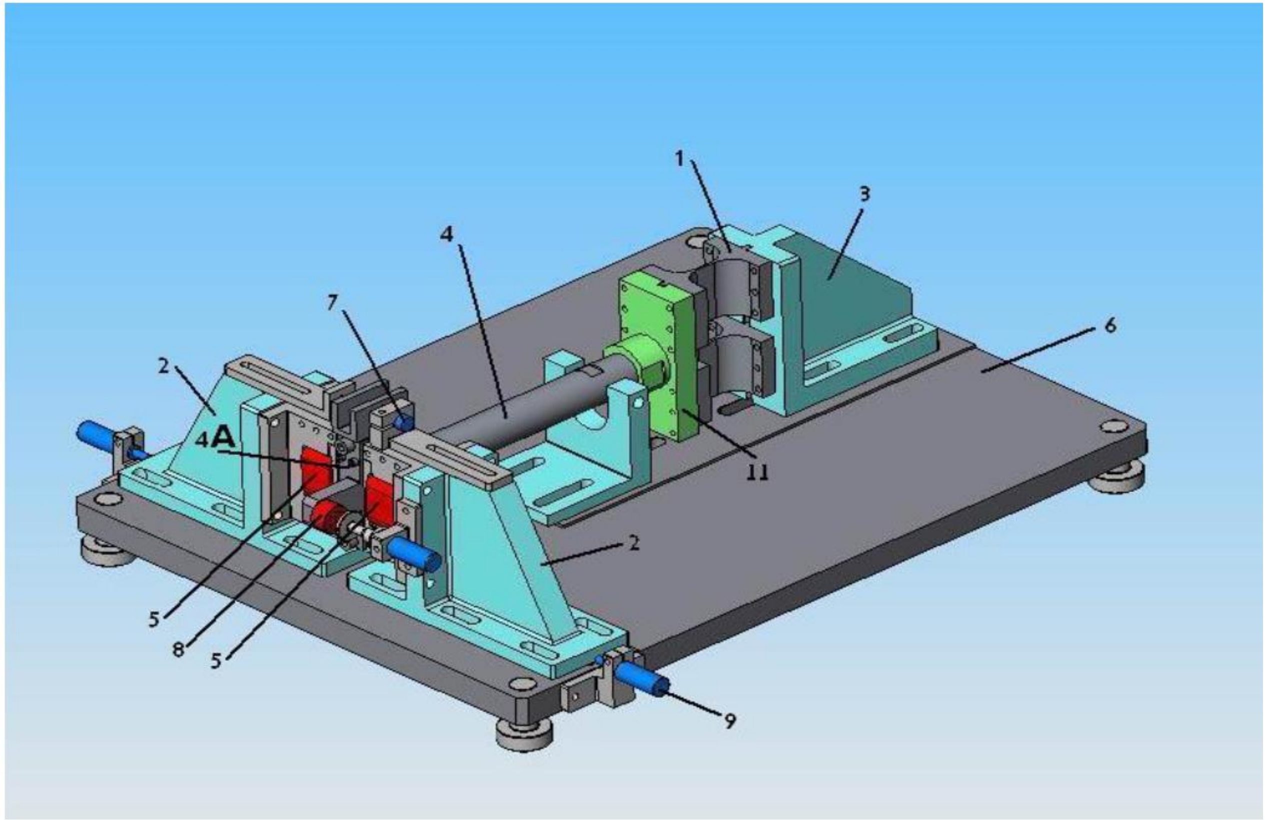
Current Amplifiers

Electromagnet actuators



EXPERIMENTAL EVALUATIONS – Test rig





S Basovich, S Arogeti, Z Brand, Adaptive output zero-bias tracking control of 1DOF AMB suspension system, 13th International Conference on Control Automation Robotics & Vision , 2014

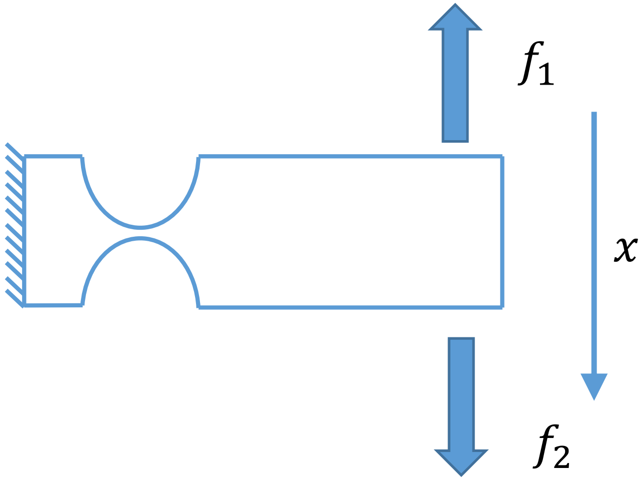
System Model

Mechanical model

Newton's second law

$$m\ddot{x} = \Sigma F$$

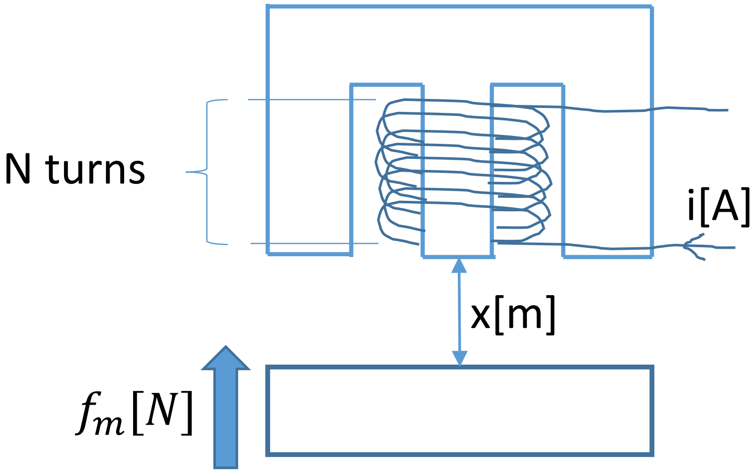
$$\boldsymbol{m\ddot{x}(t) + c\dot{x}(t) + kx(t) = f_2(t) - f_1(t)}$$



Electromagnet model

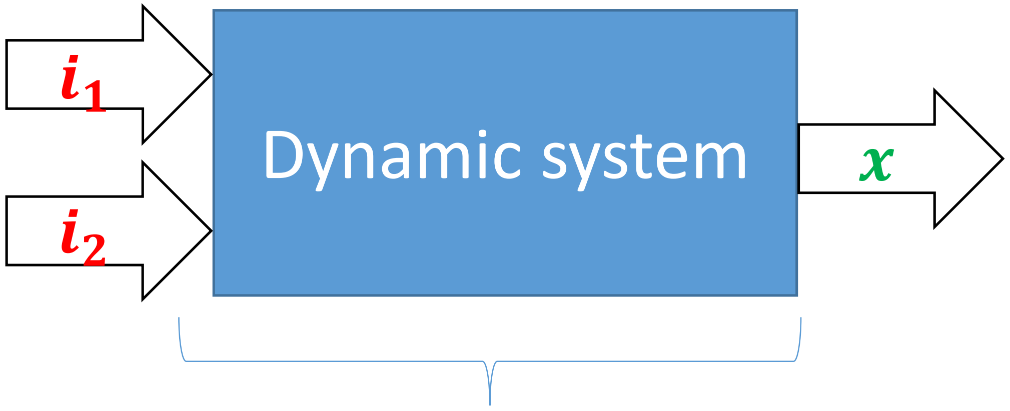
Biot-Savart law and Lorentz force

$$\left|\boldsymbol{f_{1/2}}\right| = \frac{\boldsymbol{\mu_0 A_s (Ni)^2}}{\boldsymbol{4x^2}}$$

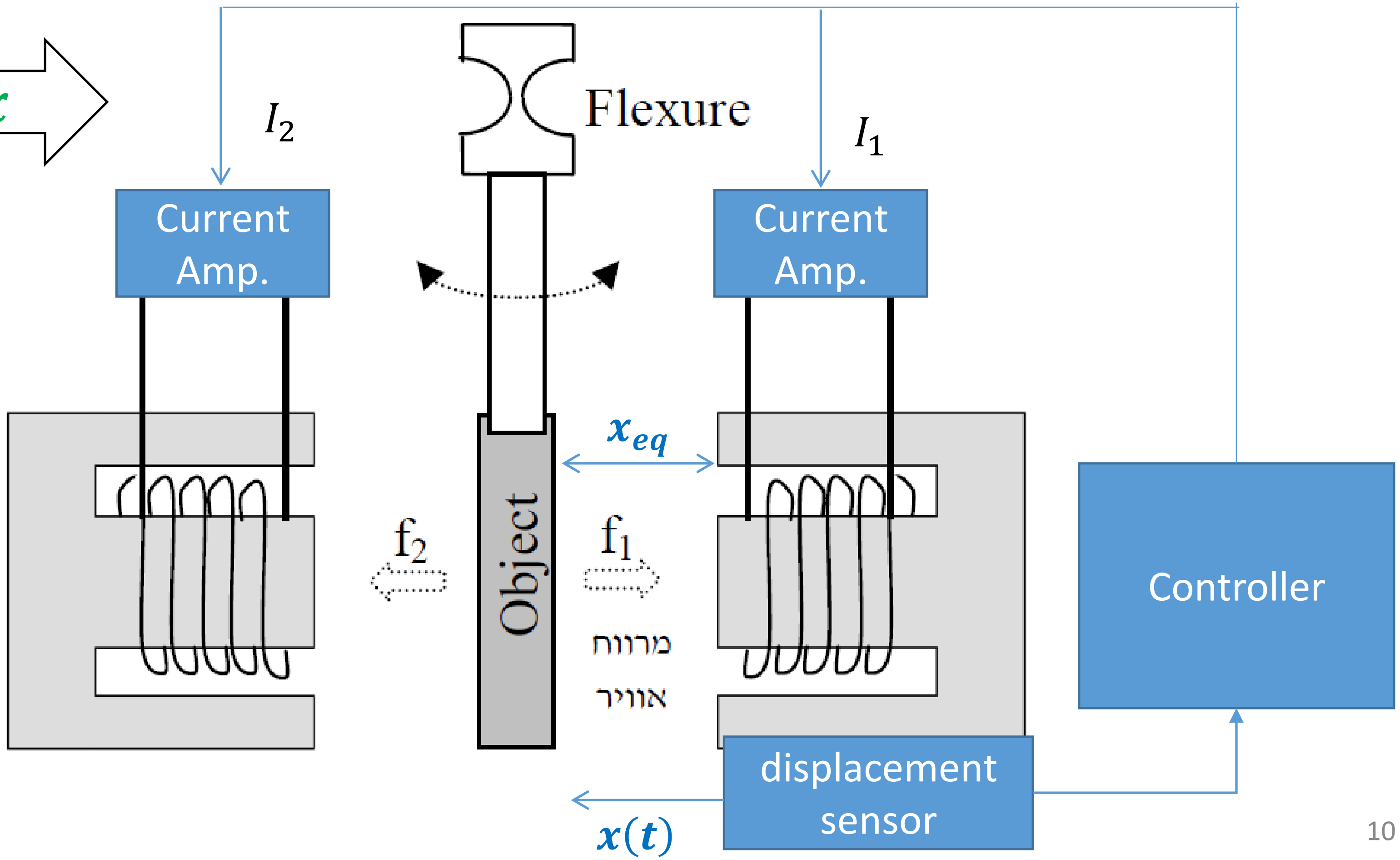


Dynamic model

$$m\ddot{x}(t) + c\dot{x}(t) + kx\,(t) = \frac{\mu_0 A_s N^2}{4}\frac{i_2^2(t)}{\left(x_{eq} - x(t)\right)^2} - \frac{\mu_0 A_s N^2}{4}\frac{i_1^2(t)}{\left(x_{eq} + x(t)\right)^2}$$



- Non-linear system
- Unstable system



Linearization - Dynamic Model

$$m\ddot{x}(t) + c\dot{x}(t) + kx\,(t) = \frac{\mu_0 A_s N^2}{4}\frac{i_2^2(t)}{\left(x_{eq} - x(t)\right)^2} - \frac{\mu_0 A_s N^2}{4}\frac{i_1^2(t)}{\left(x_{eq} + x(t)\right)^2}$$

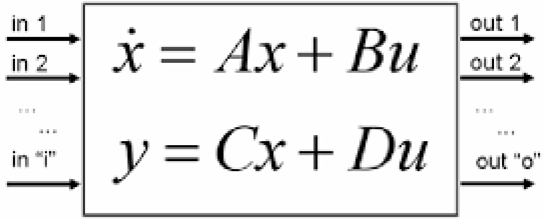
$$f\left(x_1, i_{c1}, i_{c2}\right) = f\left(x_{ep}, i_b\right) + \left.\frac{\partial f}{\partial x_1}\right|_{\substack{x_1 = x_{ep} = 0 \\ i_1 = i_2 = i_b}}\left(x_1 - x_{ep}\right) + \left.\frac{\partial f}{\partial i_1}\right|_{\substack{x_1 = x_{ep} = 0 \\ i_1 = i_2 = i_b}}\left(i_1 - i_b\right) + \left.\frac{\partial f}{\partial i_2}\right|_{\substack{x_1 = x_{ep} = 0 \\ i_1 = i_2 = i_b}}\left(i_2 - i_b\right)$$

$$\ddot{x} = \left(-\frac{4CI_b{}^2}{mL_0{}^3} - \frac{k}{m}\right)x - \frac{c}{m}\dot{x} + \frac{4CI_b}{mL_0{}^2}I_c$$

State space

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ -\frac{4CI_b{}^2}{mL_0{}^3} - \frac{k}{m} & -\frac{c}{m} \end{bmatrix} x + \begin{bmatrix} 0 \\ \frac{4CI_b}{mL_0{}^2} \end{bmatrix} I_c$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} x$$



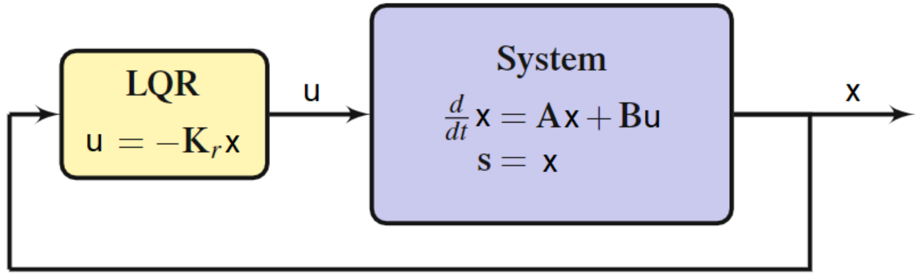
Optimal Control

$$J(u) = \int_0^\infty (x^T Q x + u^T R u)dt$$

the feedback control law that minimizes the value of the cost is: $u = -Kx$

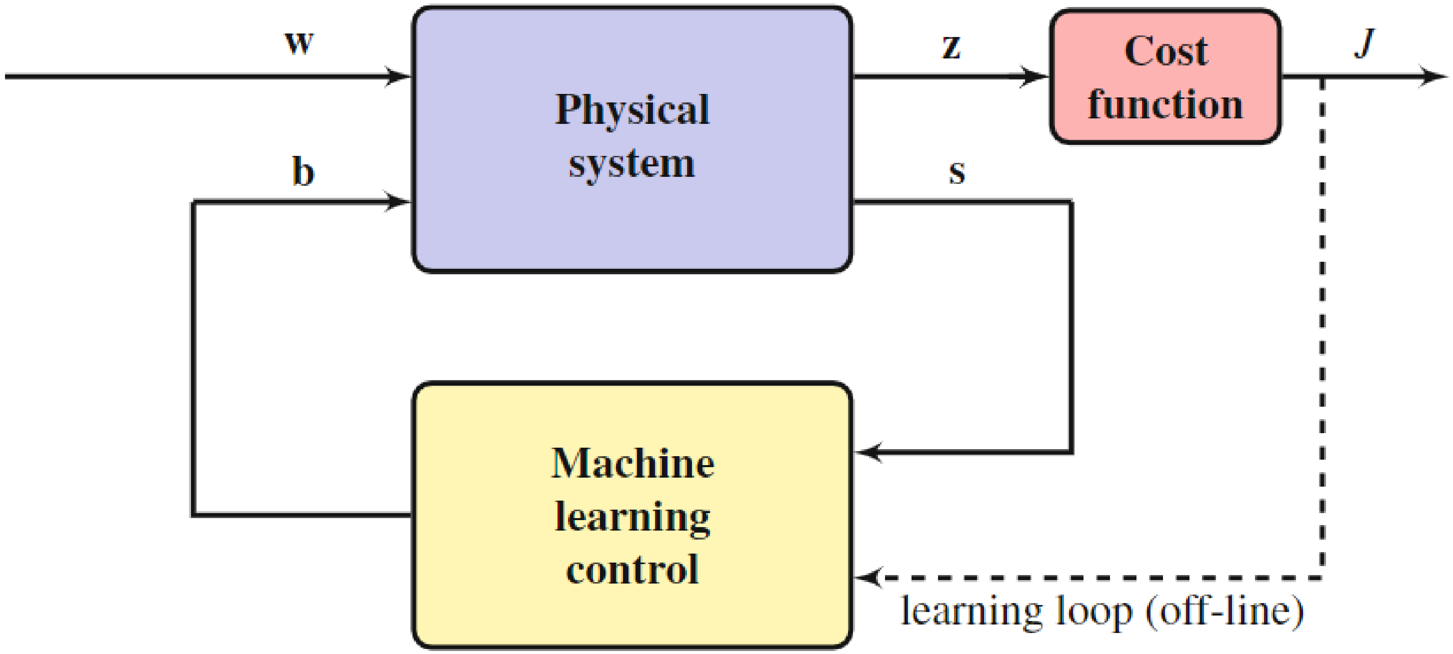
where K is given by: $K = R^{-1} B^T P$

And P is found by solving algebraic Riccati equation: $A^T P + PA - PBR^{-1} B^T P + Q = 0$

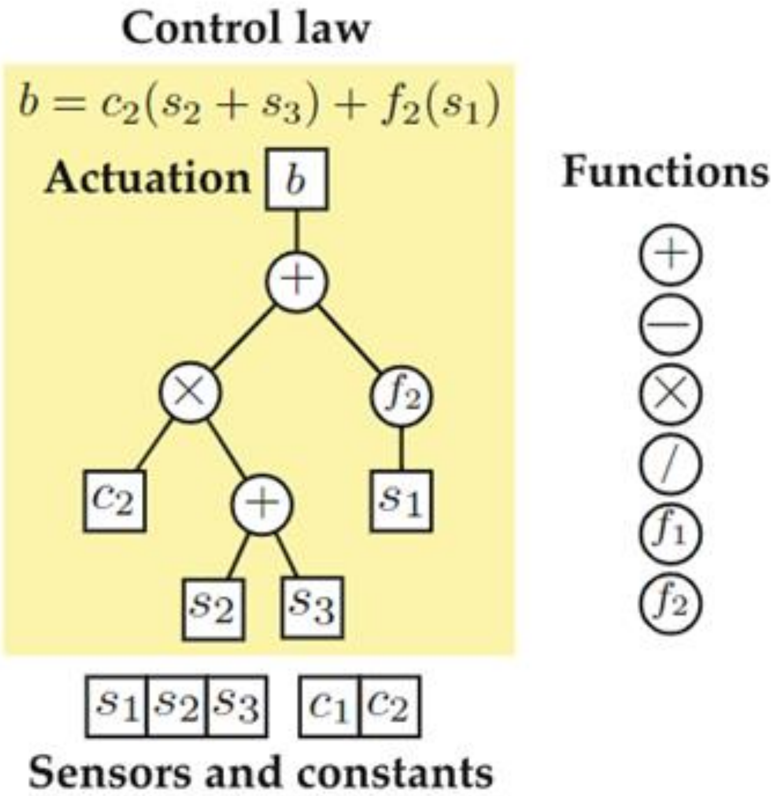


Required to know the dynamic model

Machine Learning Control Algorithm



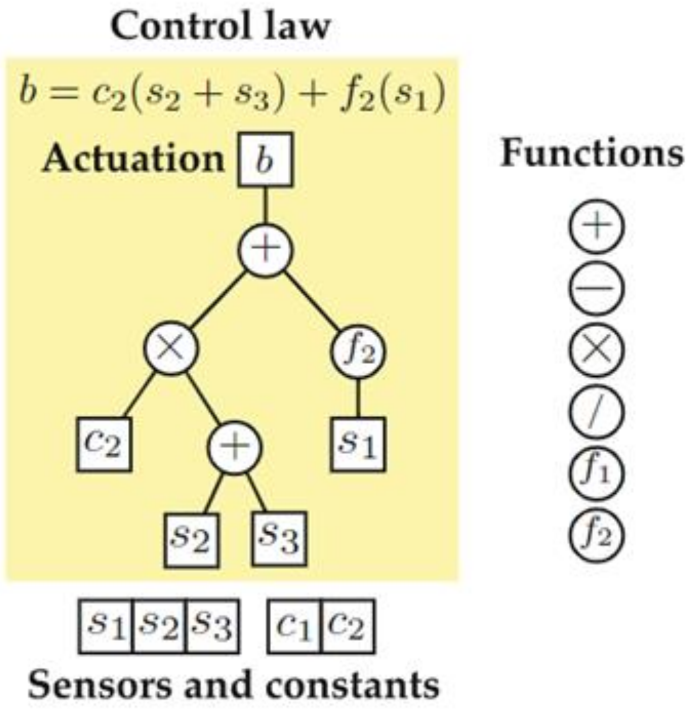
Schematic of machine learning control wrapped around a complex system using noisy sensor-based feedback.



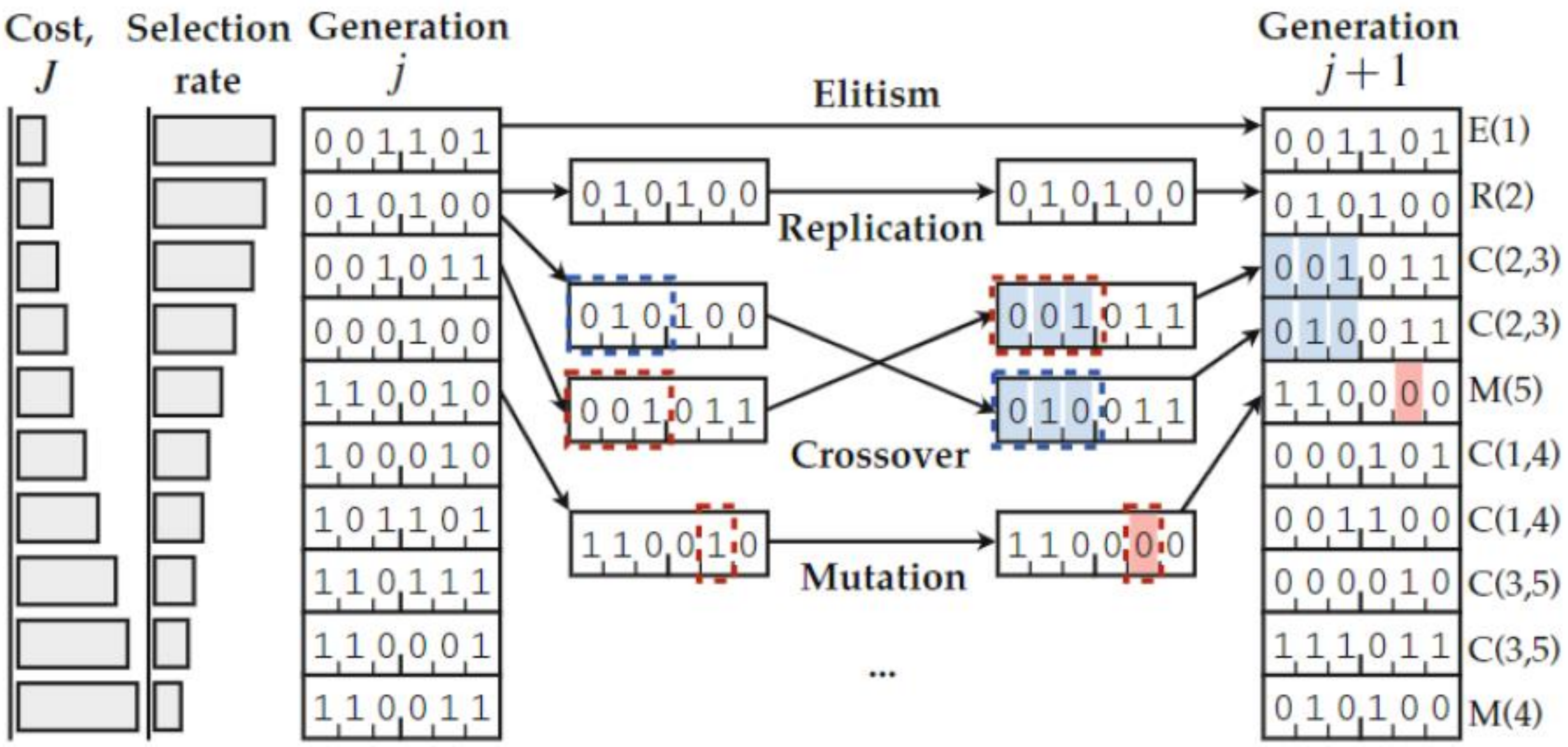
Individual function tree representation used in genetic programming.

T. Duriez et al., "Machine Learning Control - Taming Nonlinear Dynamics and Turbulence", Springer, 2017

Machine Learning Control Algorithm



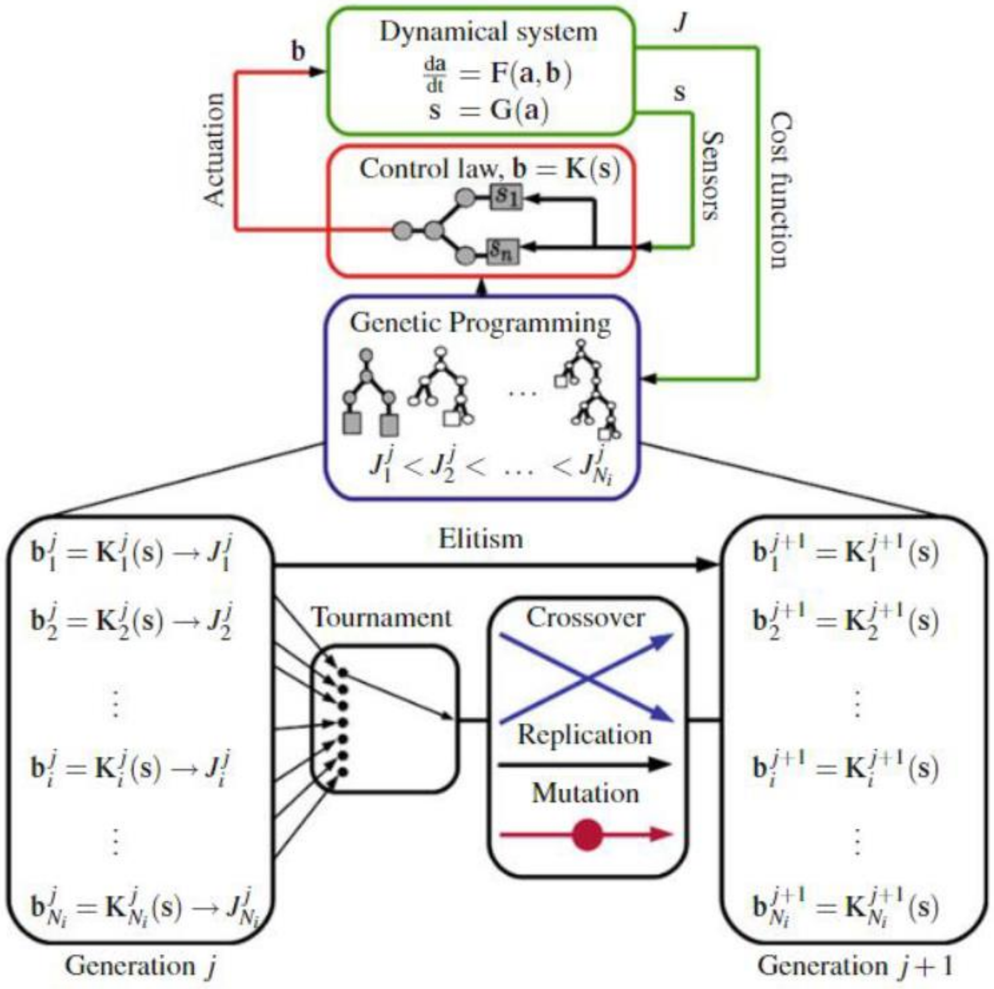
Individual function tree representation used in genetic programming.



Genetic operations to advance one generation of parameters to the next in a genetic algorithm.

T. Duriez et al., "Machine Learning Control - Taming Nonlinear Dynamics and Turbulence", Springer, 2017

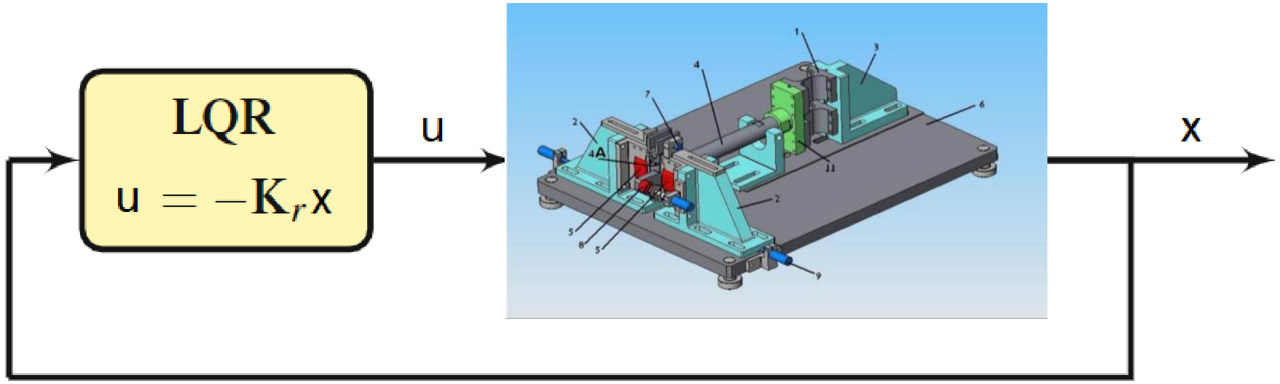
Machine Learning Control Algorithm

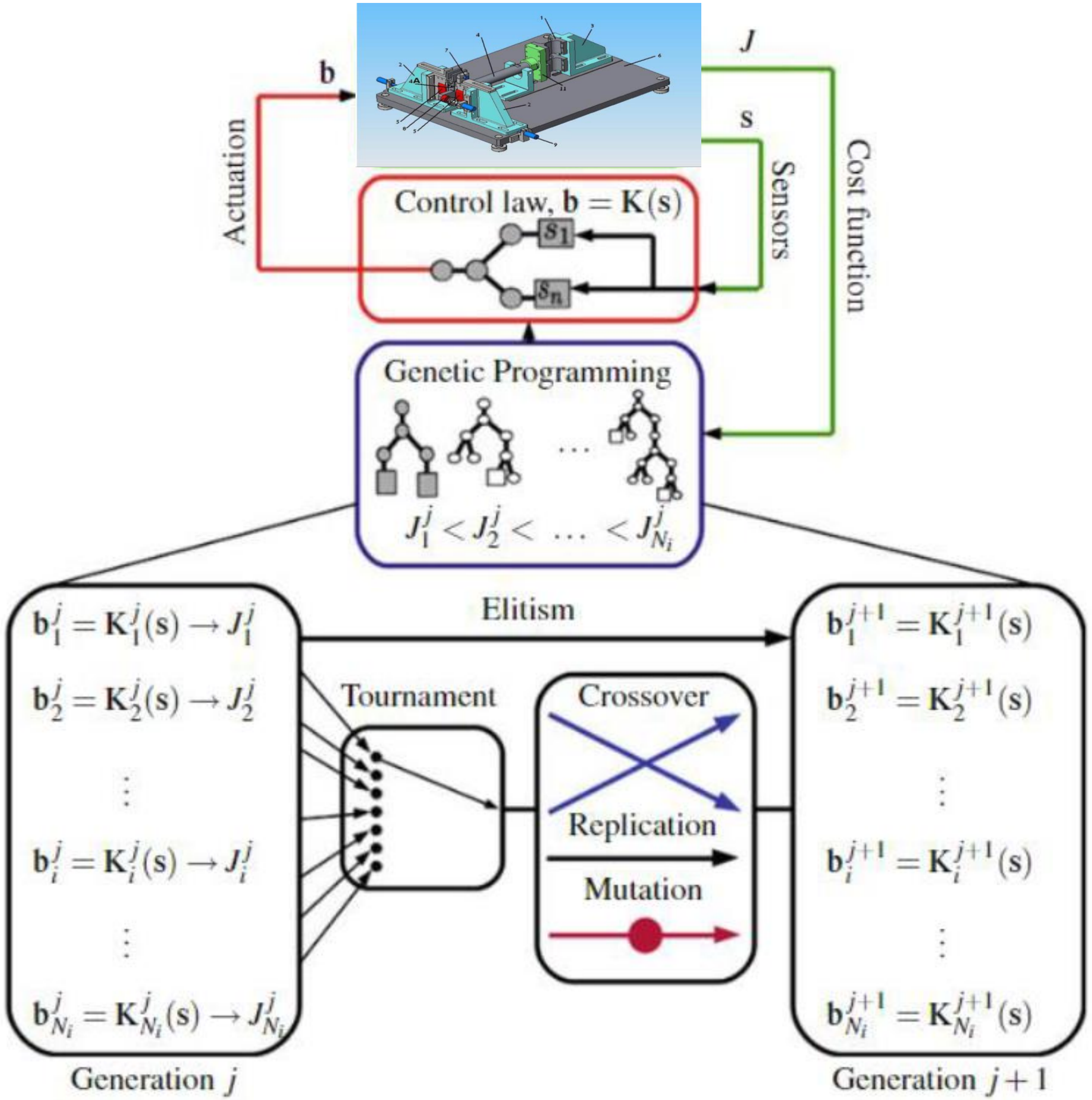


Model-free control design using GP for MLC.

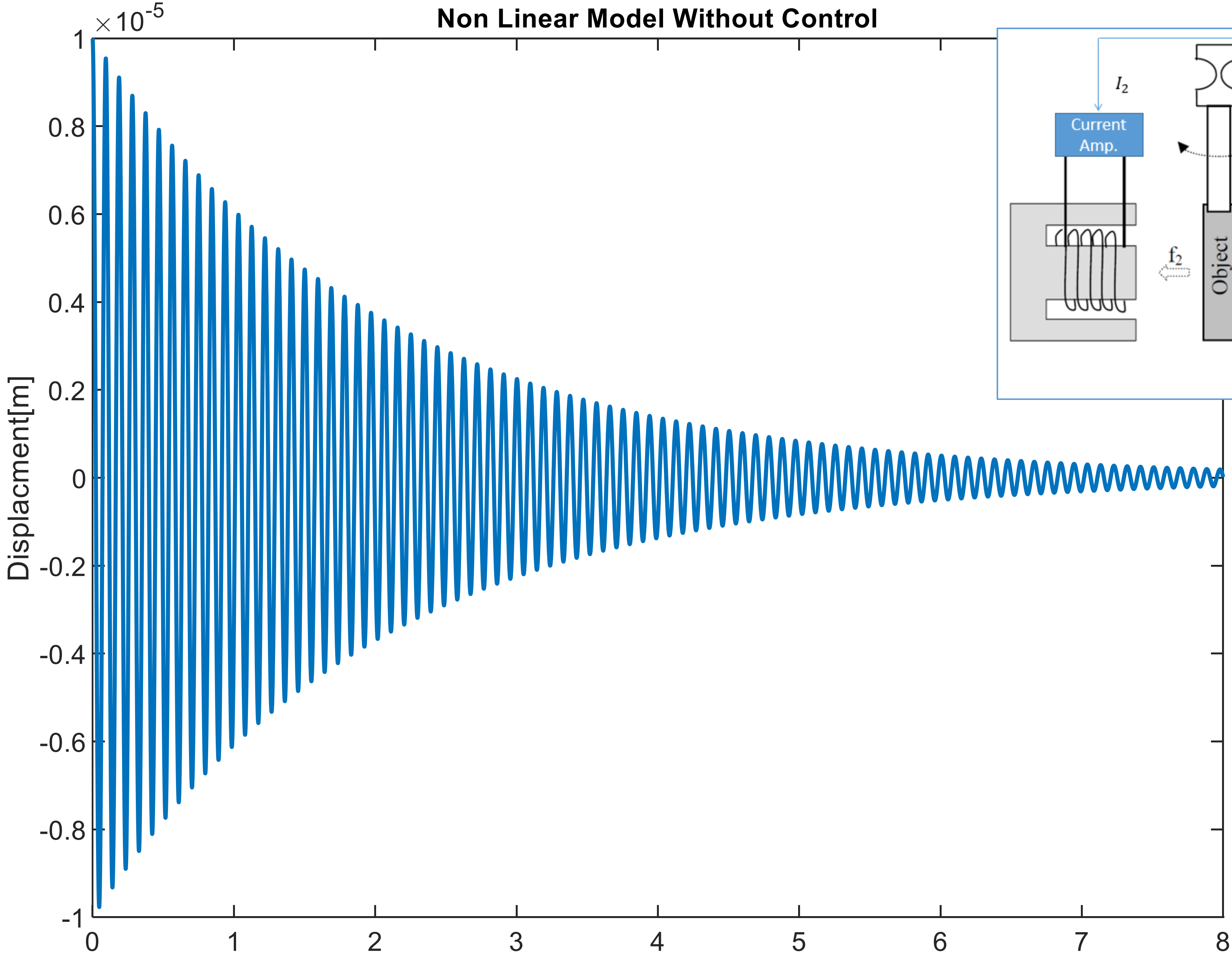
T. Duriez et al., "Machine Learning Control - Taming Nonlinear Dynamics and Turbulence", Springer, 2017

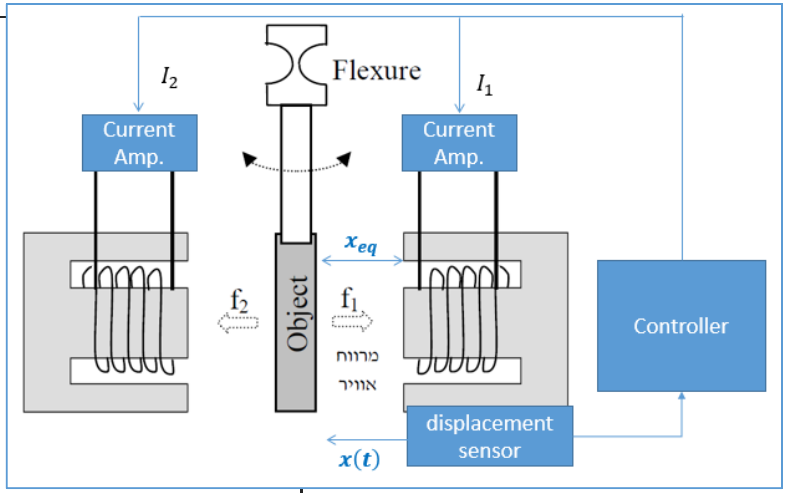
Simulation Optimal Control VS MLC





Simulation results



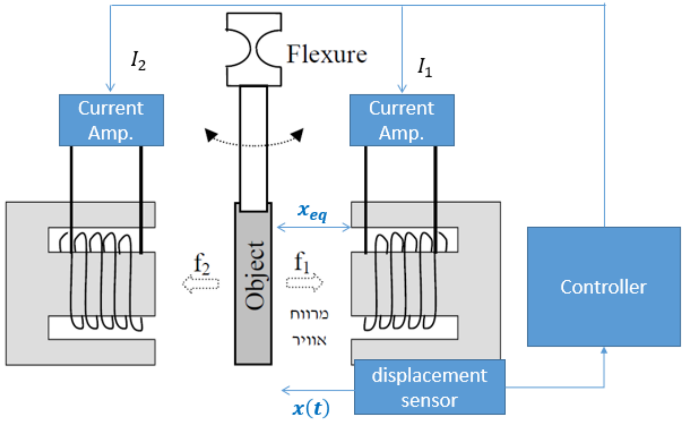


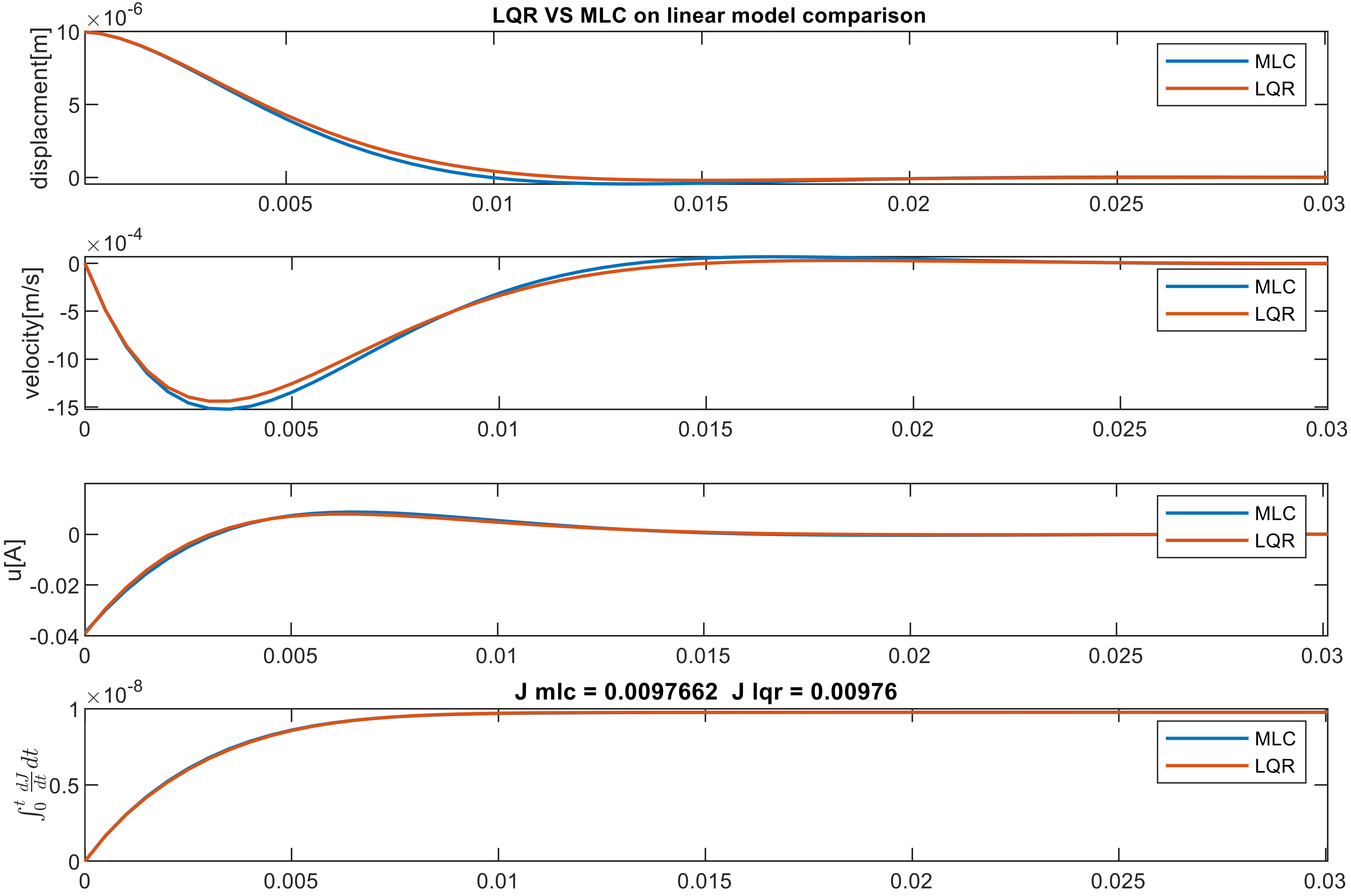
Simulation results

Mlc main parameters:
Individuals: 1000
Functions: +,x
Max Depth: 15
After 20 Generations (about an hour of calculations):

b MLC = - 3864* y(1) - 16.95 * y(2)

b LQR = -3914*y(1) -18.94*y(2)



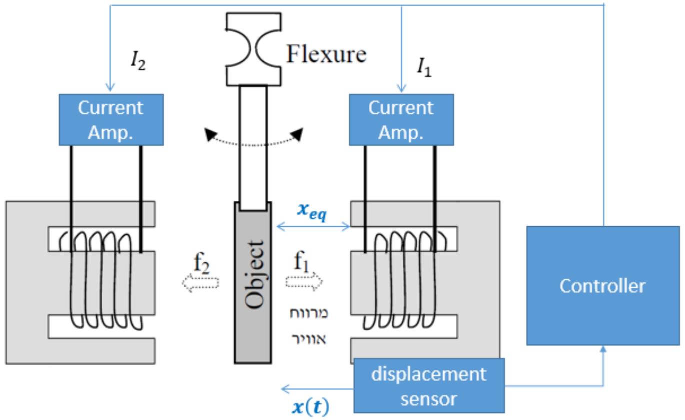


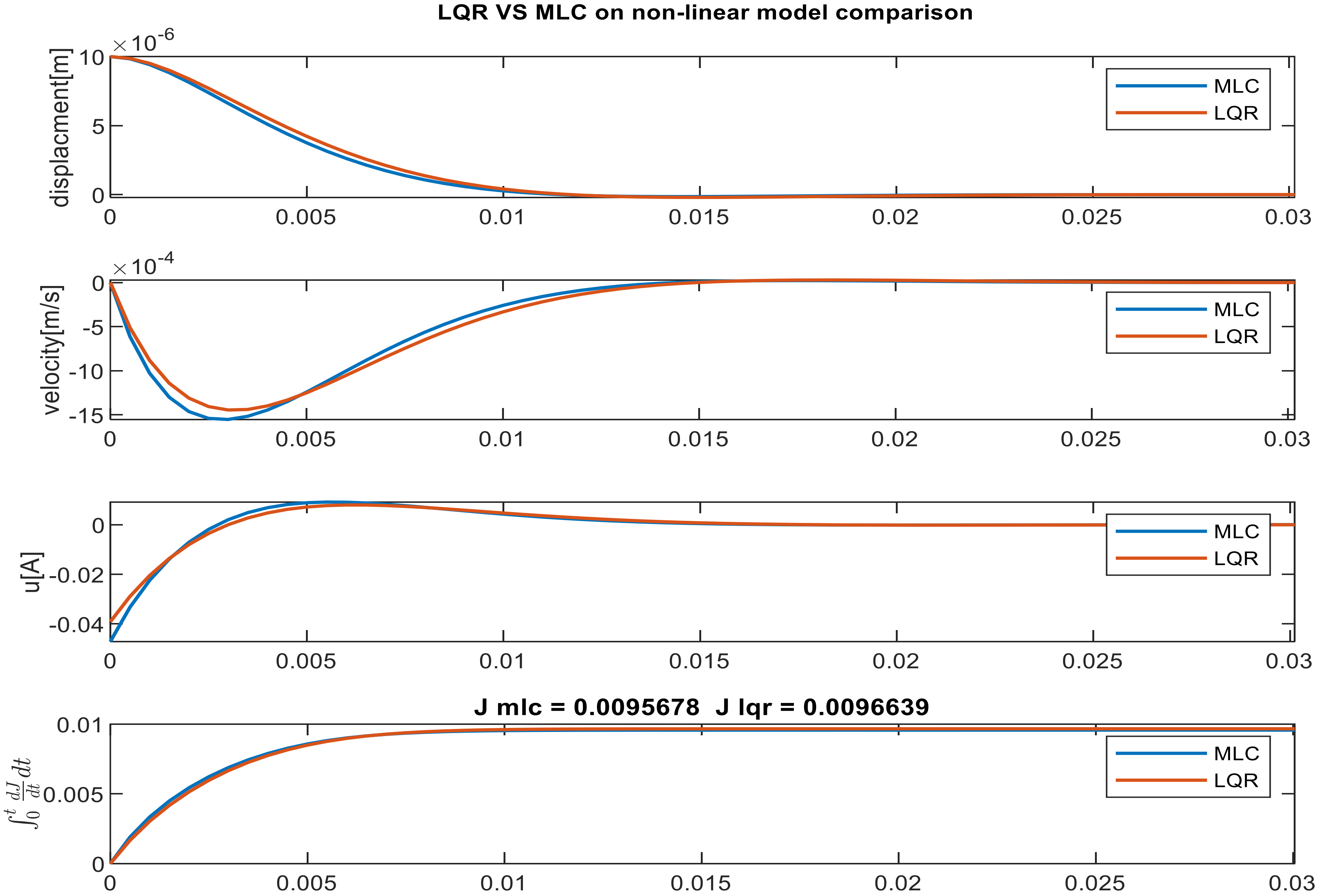
Simulation results

Mlc main parameters:
Individuals: 1000
Functions: +,x
Max Depth: 15
After 20 Generations (about an hour of calculations):

b MLC = - 4711* y(1) – 21.37 * y(2)

b LQR = -3914*y(1) -18.94*y(2)





Conclusion

- Machine-learning control results are similar to the optimal control method for the given mechanical system.

- There is potential for using machine learning control for nonlinear systems with uncertainty based on input/output data measurements.

What’s Next

- Build a framework for running the algorithm on the physical system.
- Run the experiment on the physical system.
- Compare the results to the optimal control results.
- Dynamic observer based on MLC.

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