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DRIVING INNOVATION IN MANUFACTURING

MECO RESEARCH TEAM

A BRIEF HISTORY OF OPTIMIZATION-BASED ILC. WHAT'S NEXT?

17/03/2022 @ Syscop, University of Freiburg

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Outline

Introduction

Opt-ILC: a brief history

- Filter based an Model-inversion ILC
- Norm-Optimal ILC
- Optimization based ILC
- RoFaLT

Applications and developments

- Applications
- Multi-system ILC
- ECOset-ILC

Conlcusion

Outline

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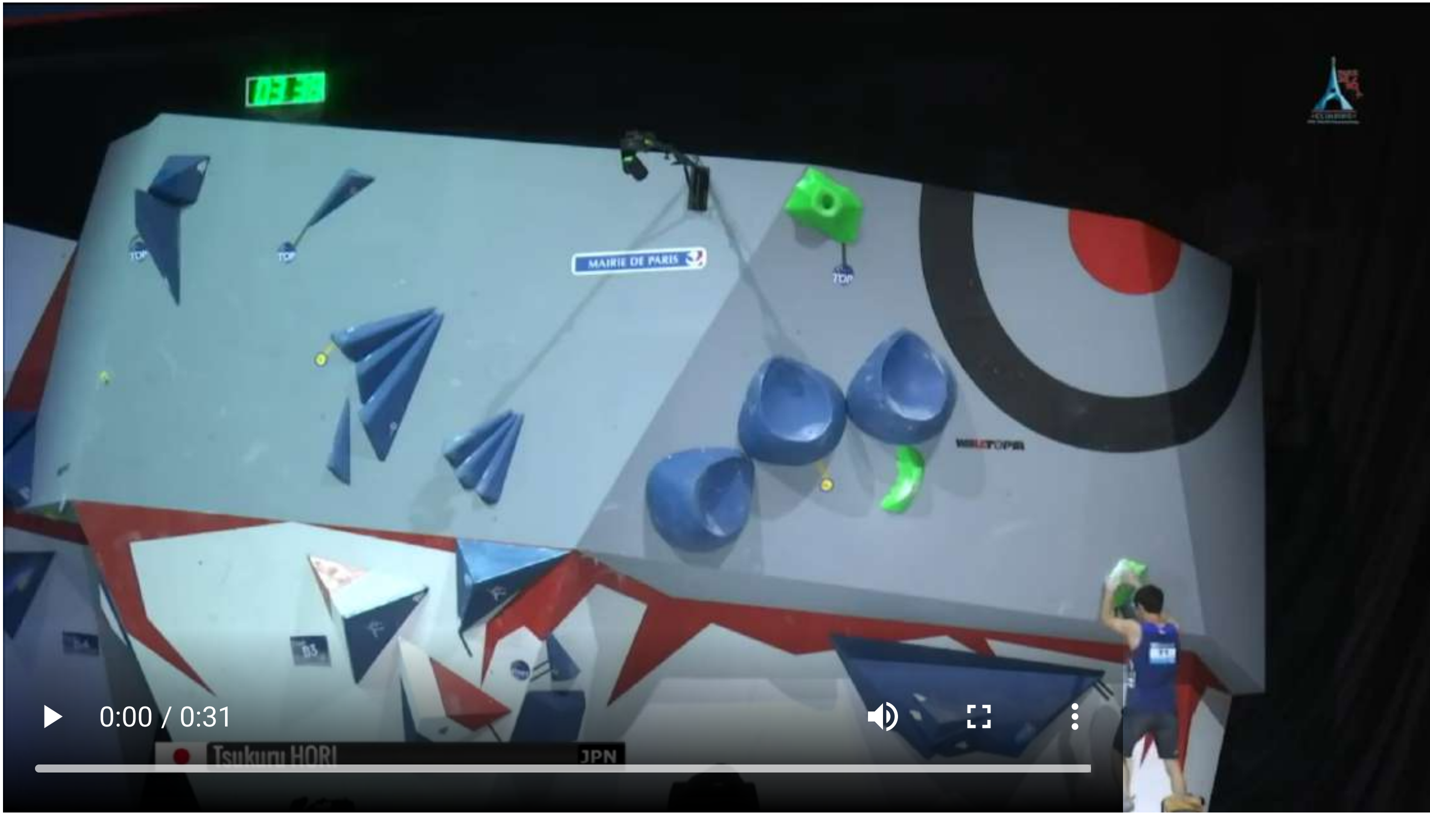
What is ILC?



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What is ILC?

- learn from previous trials and improve
- offline strategy
- Feed-foward/open-loop
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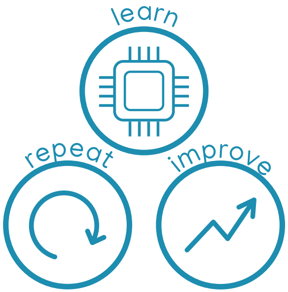

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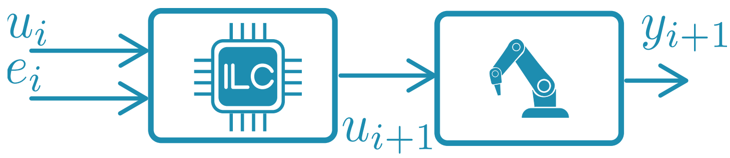

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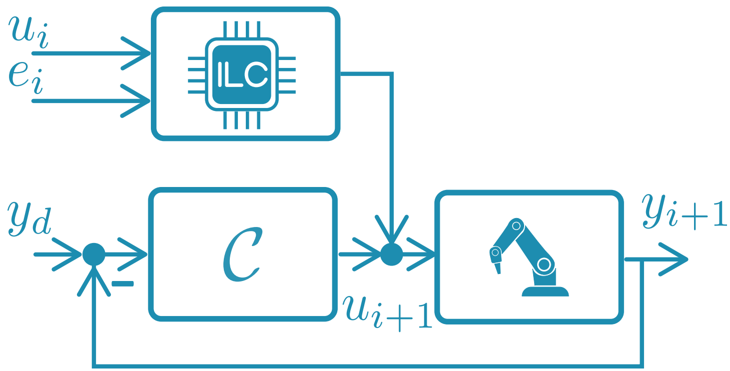

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- same initial conditions
- compensate repetitive errors
  - model-plant mismatch
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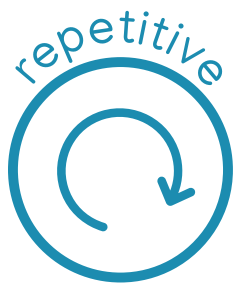

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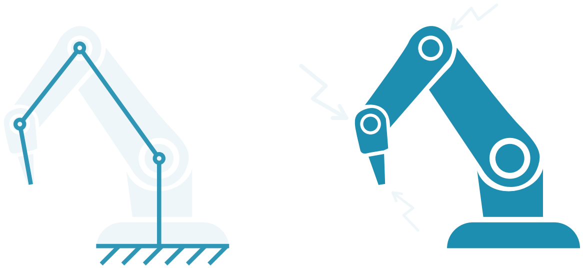

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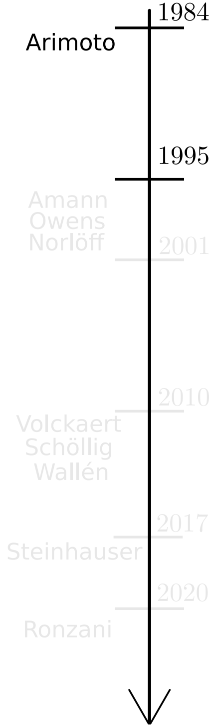
Opt-ILC: a brief history

From $\mathcal{LQ}$ -filter to norm-optimal ILC

How to get fast convergence and high performance?

Model-inversion



OPT-ILC: A BRIEF HISTORY

From $\mathcal{L}\mathcal{Q}$ -filter to norm-optimal ILC

$$u_{i+1} = \mathcal{Q}\big(u_i + \mathcal{L}\,e_i\big)$$

$$e_i = y_d - y_i$$

How to get fast convergence and high performance?

⇩

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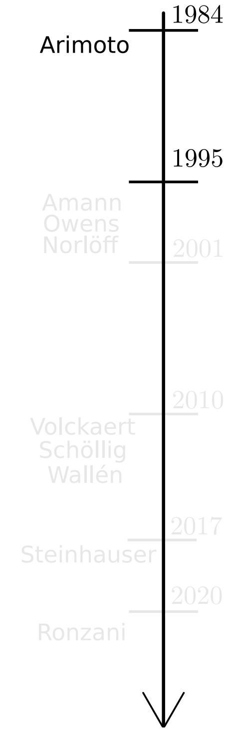

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robustness learning filter

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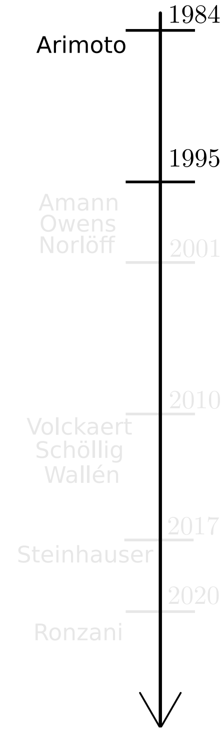

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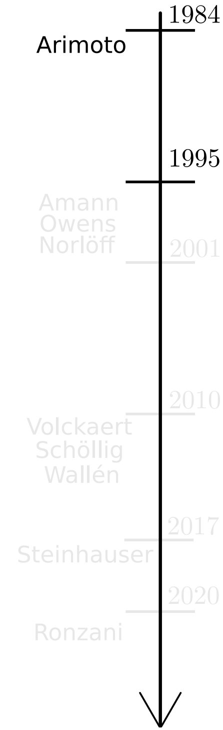

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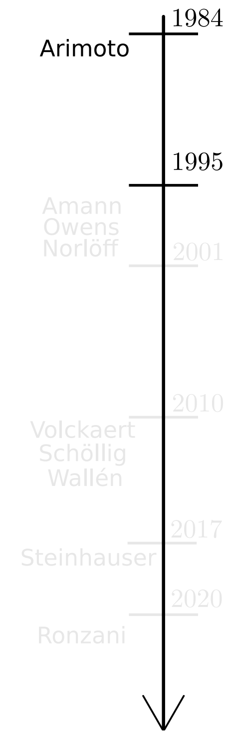
$$\mathcal{Q} = I \qquad \mathcal{L} = P^{-1}$$



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$$u_0 = 0$$

$$y_0 = 0$$

How to get fast convergence and high performance?

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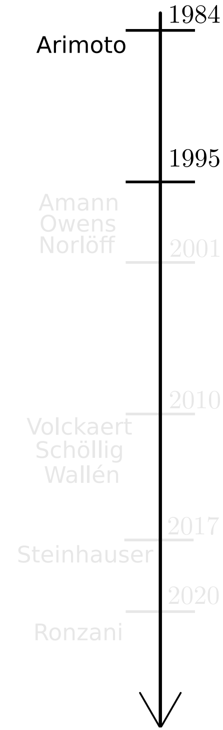

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$$u_1 = I\left(0 \ + P^{-1} y_d\right)$$

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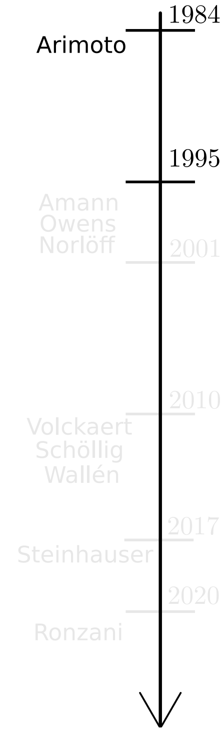

Opt-ILC: a brief history

From $\mathcal{L}\mathcal{Q}$ -filter to norm-optimal ILC

- Optimal control approach
- In practice:
- Equivalence in the filter design framework:

$$\mathcal{Q} = \left(\hat{P}^T Q \hat{P} + R_1 + R_2\right)^{-1} \left(\hat{P}^T Q \hat{P} + R_2\right)$$

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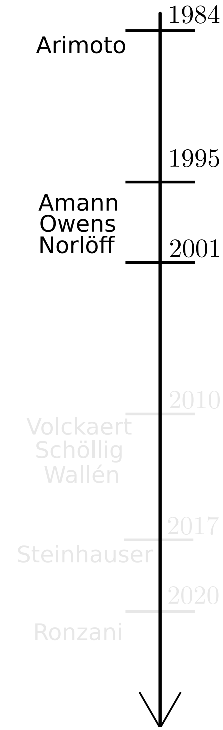
Can this be generalized even further?



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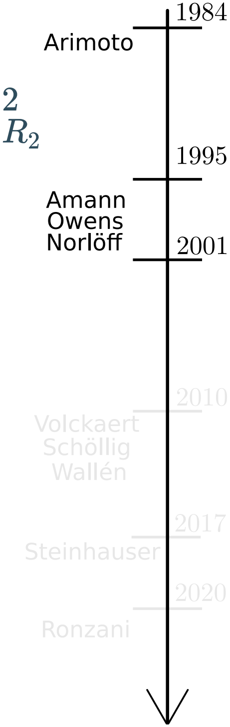

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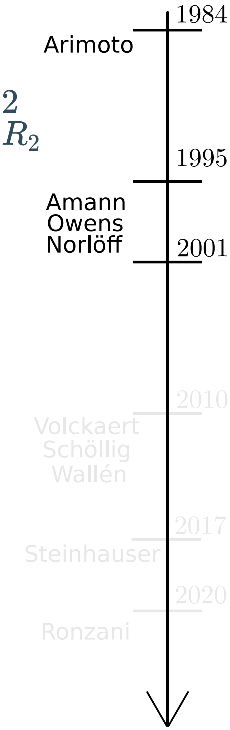

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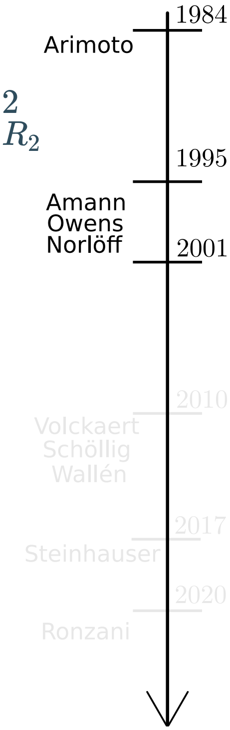

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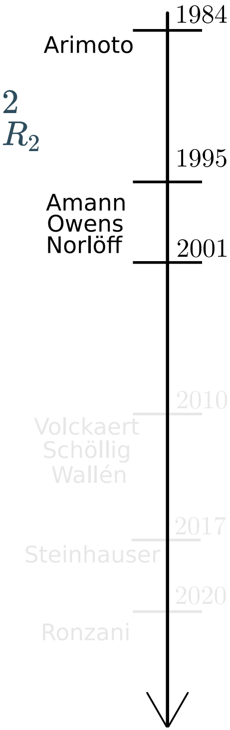

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ocp

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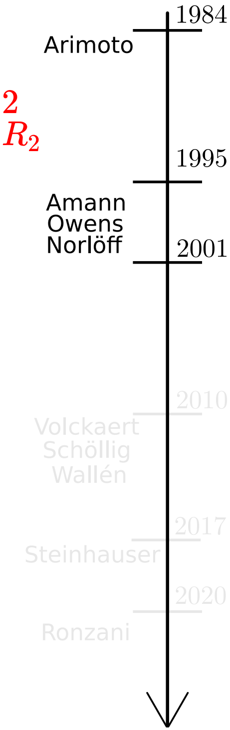

OPT-ILC: A BRIEF HISTORY

Optimization-based ILC

- Model correction

$$\beta_i = \arg\min_{\beta} \|y_i - \hat{\mathcal{P}}(u, \beta)\|_V^2 + \|\beta\|_{W_1}^2 + \|\beta - \beta_{i-1}\|_{W_2}^2$$

  - Observer-based/Kalman filter estimation
  - Disturbances/parameter estimation

- Model inversion

$$u_{i+1} = \arg\min_{u} \|y_d - \hat{\mathcal{P}}(u, \beta_i)\|_Q^2 + \|u\|_{R_1}^2 + \|u - u_i\|_{R_2}^2$$

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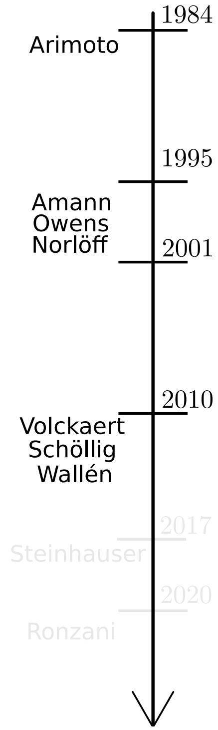

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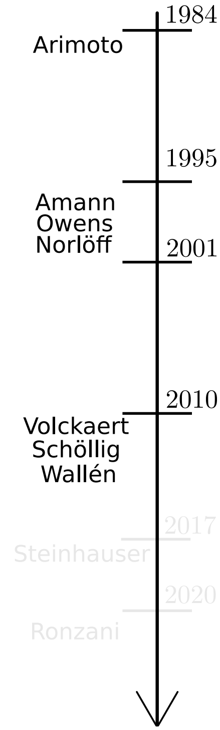

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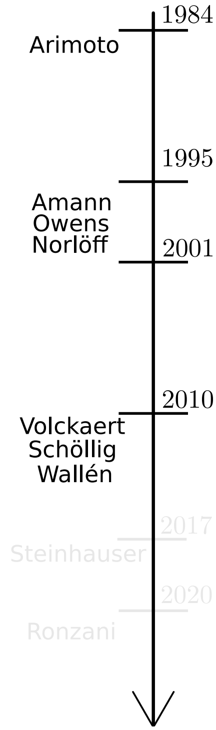
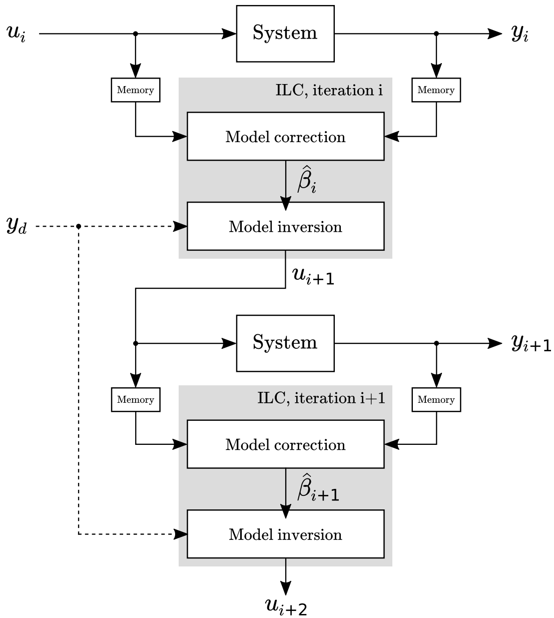
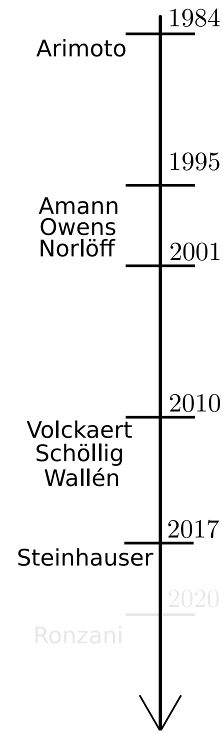


OPT-ILC: A BRIEF HISTORY

RoFaLT: two-step nonlinear ILC




```
myRoFaLT = rofalt.RoFaLT();

doc rofalt.RoFaLT

model = myRoFaLT.setModel('ts', 0.01, ...
                          'ode', odeFcn, ...
                          'output', yFcn);

ilc = myRoFaLT.setController('ilc');

ilc.setReference(ref);

ilc.control.addInequalityConstraints(usym, ...
                                     umin, umax)

for i = 1:1:nTrials

  umeas = ilc.runIteration(struct('u', umeas, ...
                                  'y', ymeas));

  ymeas = executeMeasurements(umeas);
end

results = ilc.getResults();
```



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  - Input correction
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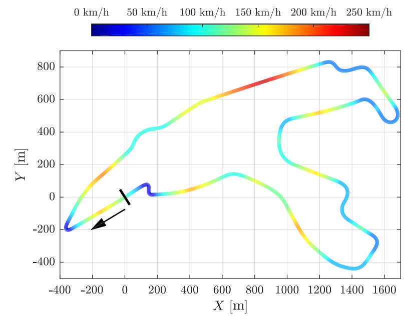
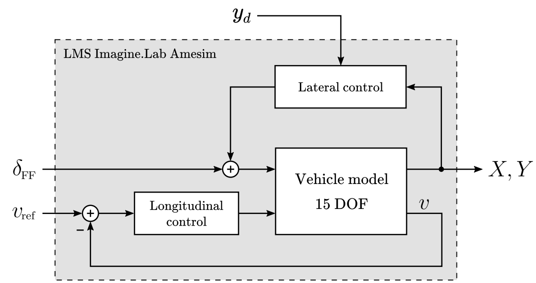
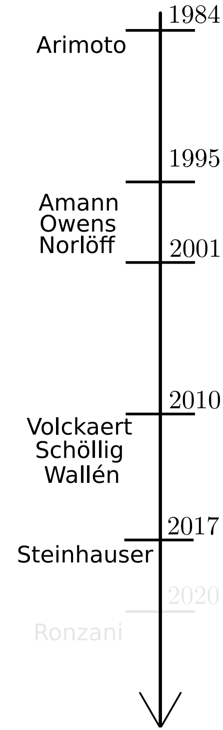
  - Constraints: input saturation







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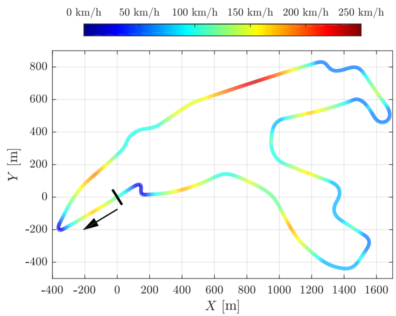

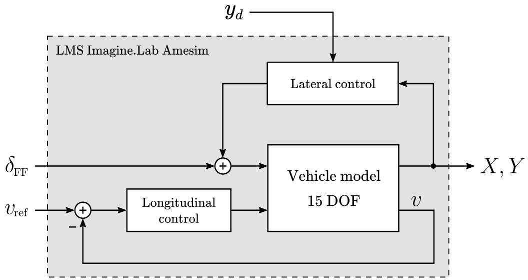

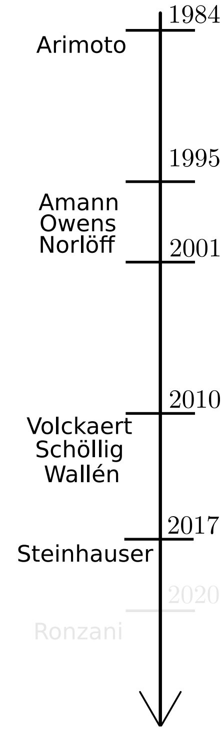

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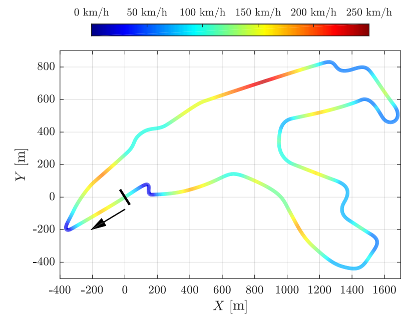

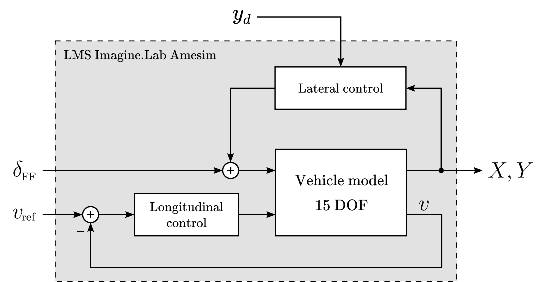

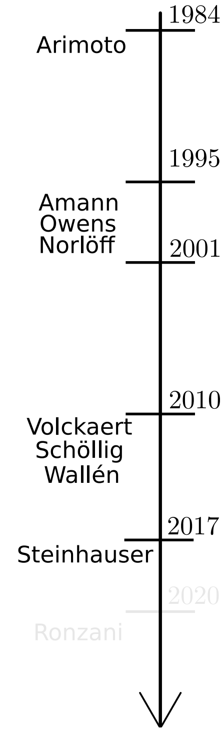

Applications

Time-optimal path tracking

- Model correction
  - Manipulator inverse dynamics
  - Torque input correction
- Model inversion
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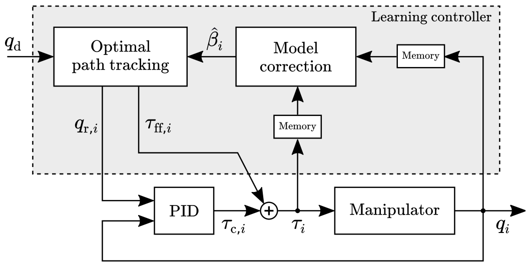
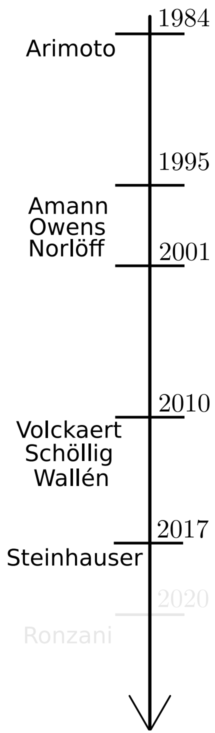
  - Path-tracking





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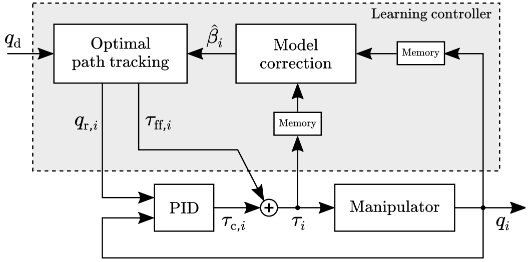

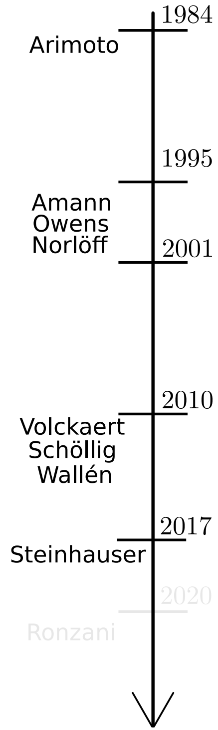

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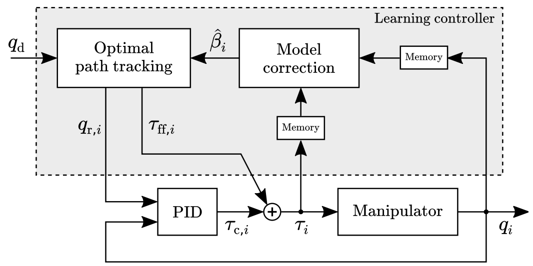

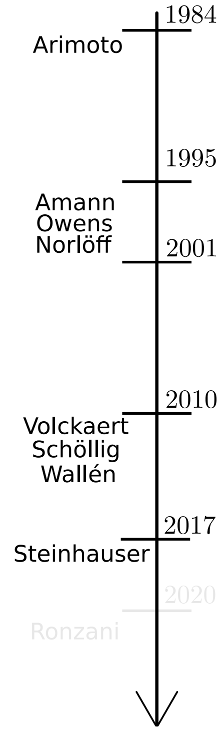

DEVELOPMENTS

- Fleet of mechatronic systems
- Repetitive task
- Iterative Learning Control

+

- Industry 4.0: interconnected systems

⇩

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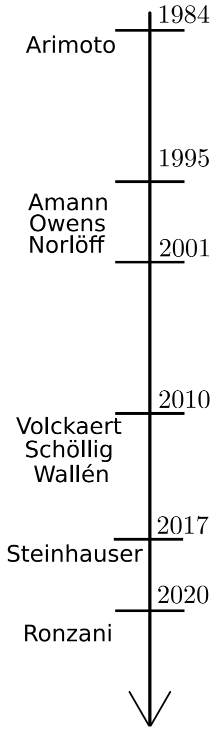

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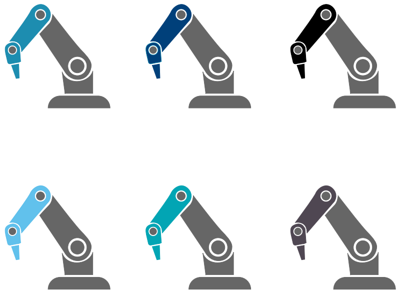

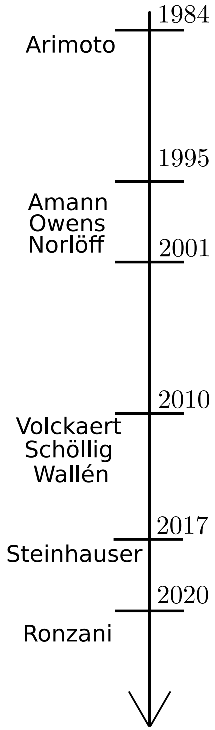

Developments

- Fleet of mechatronic systems
- Repetitive task
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+

- Industry 4.0: interconnected systems

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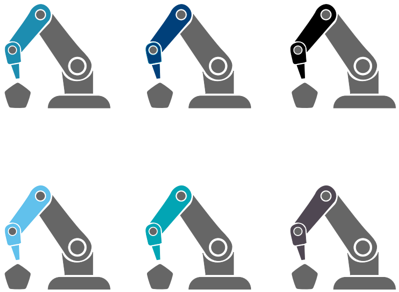

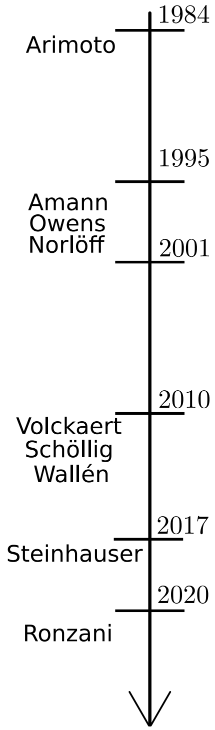

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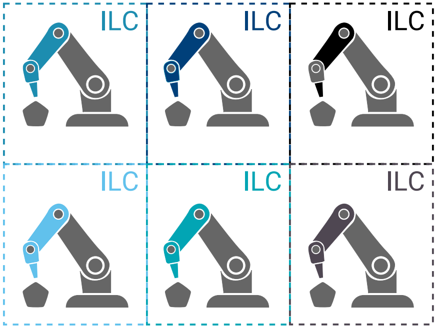

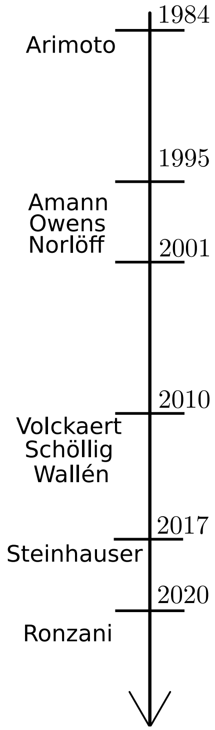

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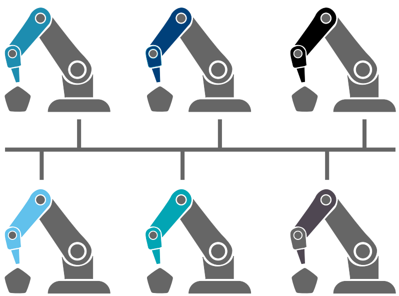

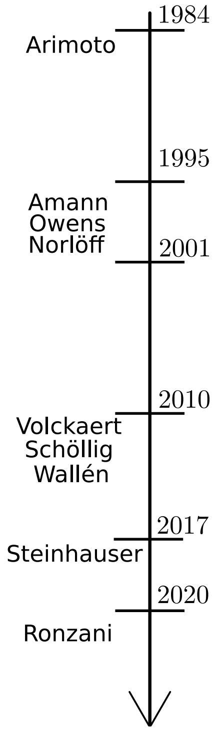

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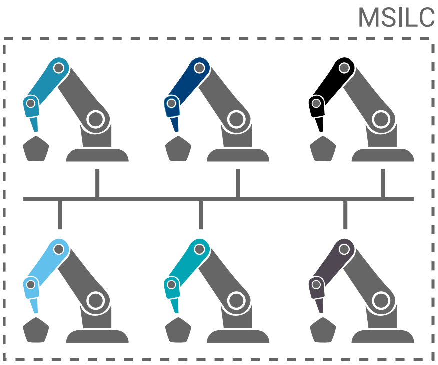
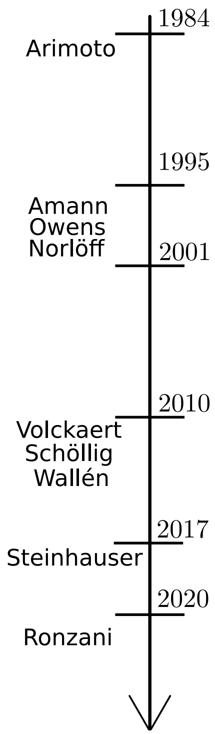
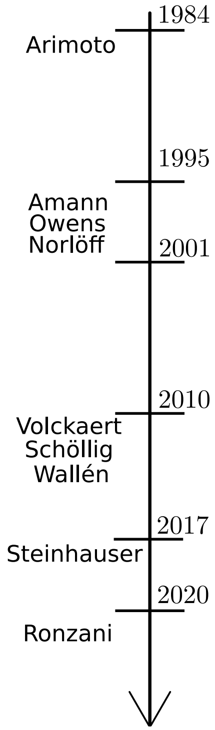




Developments

Multi-system ILC

- Model correction: common+delta
- Common ILC vs. Single ILC update
- Performances:
  - $\propto$ similarity of fleet
  - Common ILC reduces iteration-varying disturbances



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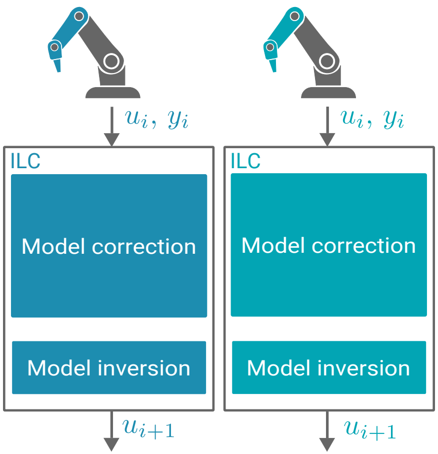

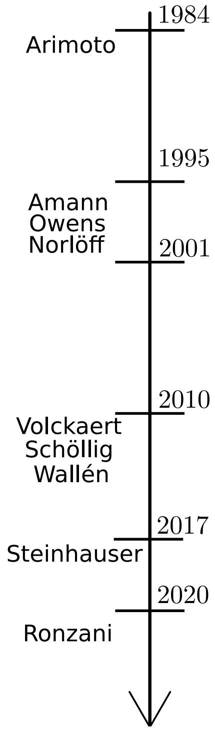

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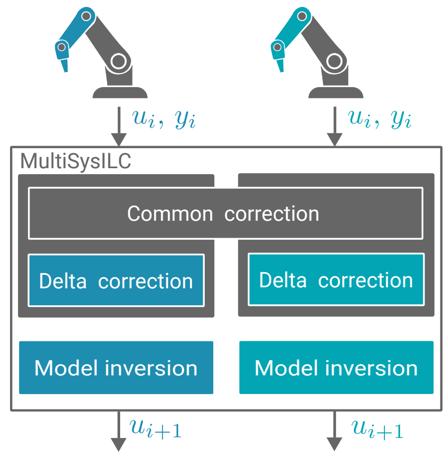

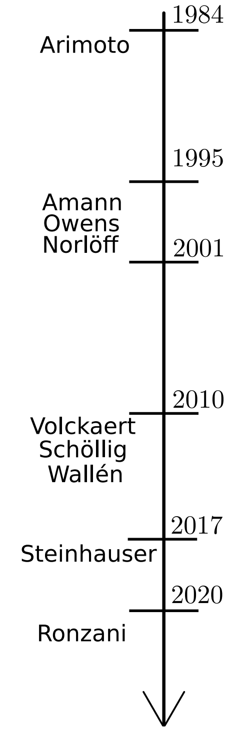

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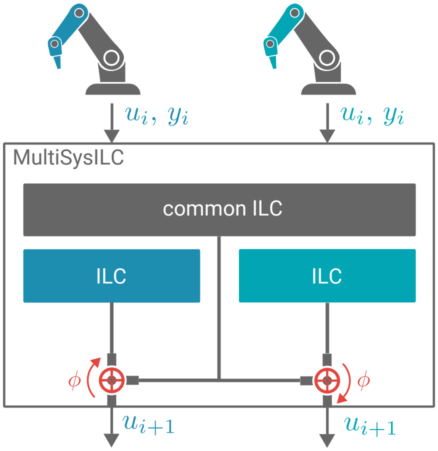

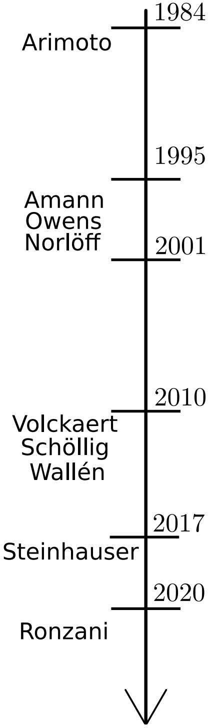

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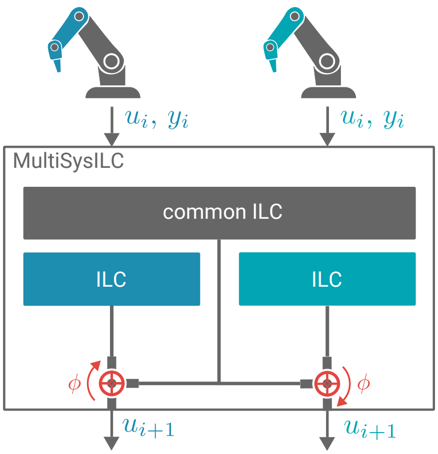

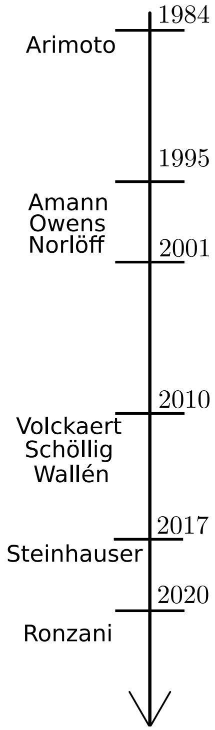

DEVELOPMENTS

ECOset-ILC

- Mechatronic system
- Repetitive task
- Iterative Learning Control

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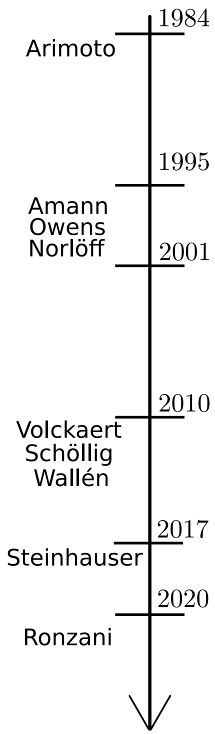
- Low-informative sensor (binary/multi-valued)
  - Hall-effect sensors
  - Photoelectric sensors sensors



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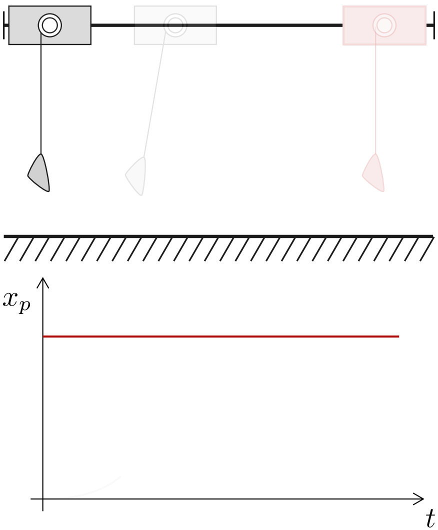

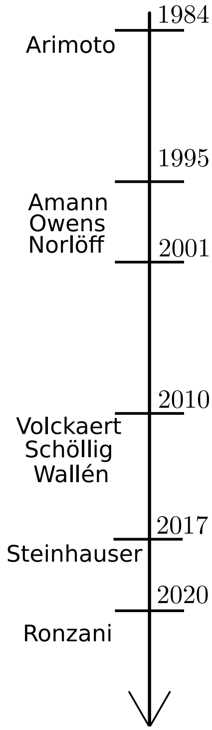

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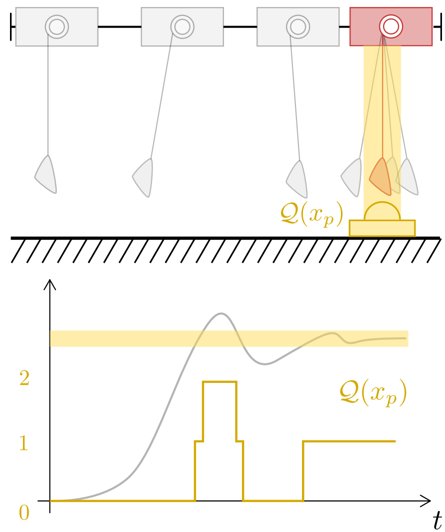

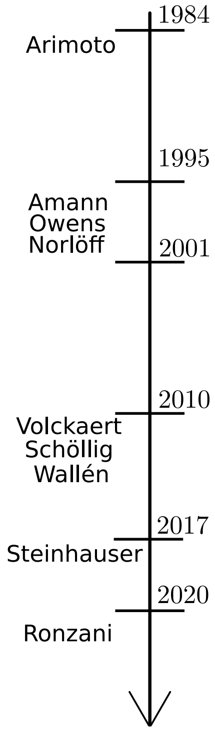

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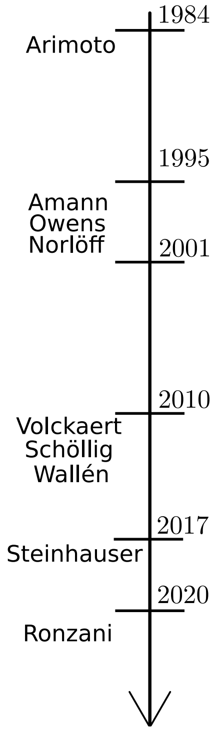
ECOset-ILC

- Set-Membership Estimation
  - Binary/multi-valued output as bounded-noise
  - Parameter set estimate
  - Semi-infinite programming
- Optimal control problem
  - Control Performance (tracking, time-optimal)
  - Optimal Design of Experiments
  - Bilevel Optimization Problem



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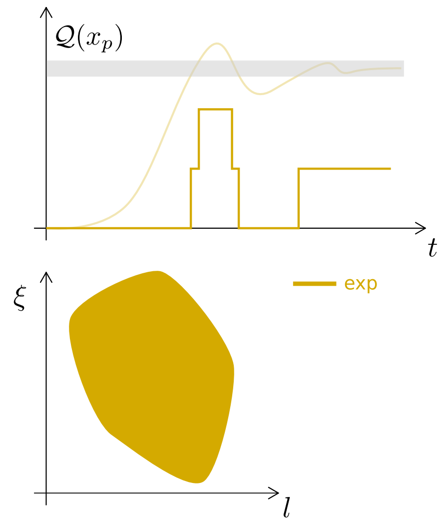

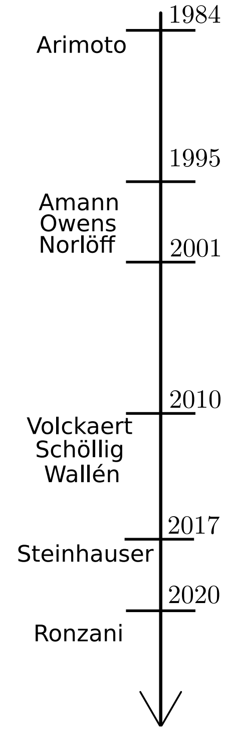

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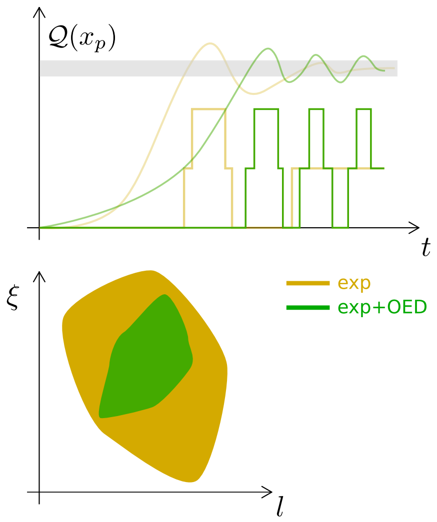

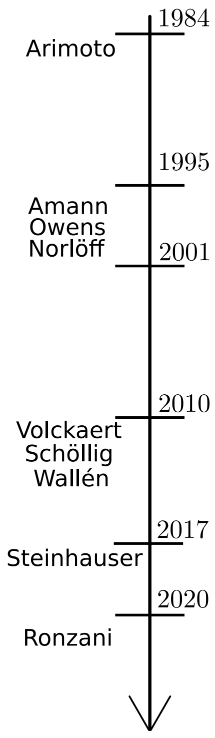

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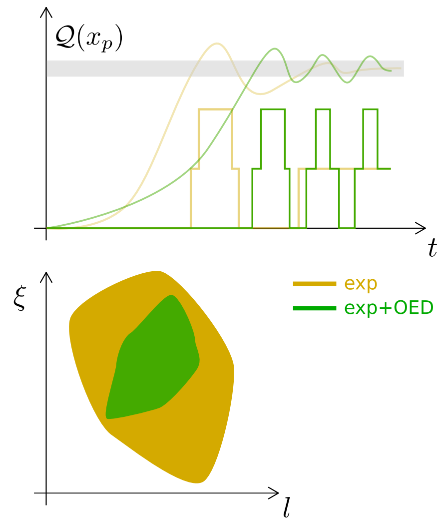

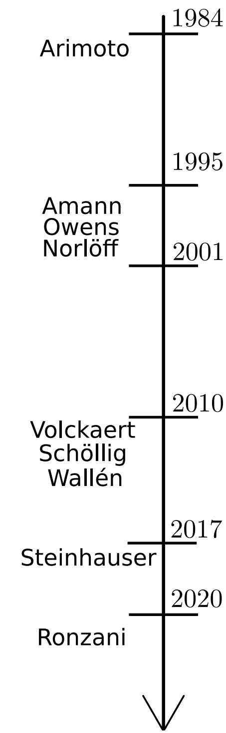

Next?

Task flexibility in ILC

- Model
- Explicit corrections terms
  - non-parametric corrections: β represents a disturbance
  - parametric corrections: β adapts physical parameters
- How to combine this correction to trade-off performance vs flexibility?

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Task flexibility in ILC

- Model

$$\hat{\mathcal{P}} : \begin{cases} x(k+1) = f(x(k), u(k)) \\ y(t) = h(x(k), u(k)) \end{cases}$$

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$$\hat{\mathcal{P}} : \begin{cases} x(k+1) = f(x(k), u(k)) \\ y(t) = h(x(k), u(k)) + \beta(k) \end{cases}$$

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- Norm-Optimal ILC
- Optimization based ILC
- RoFaLT

Applications and developments

- Applications
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- ECOset-ILC

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CONCLUSION

Stability and convergence analisys

- Model correction: additive disturbance (no optimization problem)
- Model inversion: Tracking error minimization
- Linear system dynamics

$\Downarrow$

$\mathcal{LQ}$ framework analysis

Conclusion

Stability and convergence analisys

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ZOO-ILC (Baumgärtner, Diehl 2020)

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References

A brief history of pptimization-based ILC

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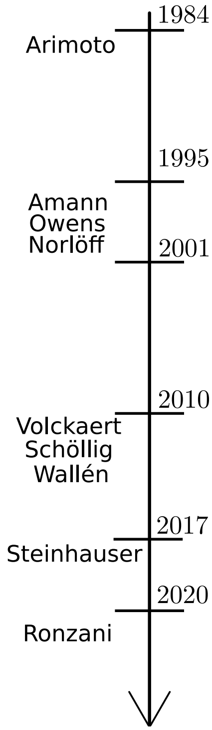

Thank you for your attention.

Questions? daniele.ronzani@kuleuven.be