

Slovak University of Technology in Bratislava
Institute of Information Engineering, Automation, and Mathematics



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Introduction to Machine Learning in Process Control

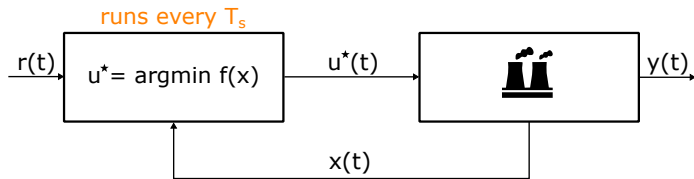
Applications of ML in Process Control

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- **Lecture:** Martin Klaučo, `martin.klauco@stuba.sk`
- **Exercises:** Patrik Valábek, `patrik.valabek@stuba.sk`

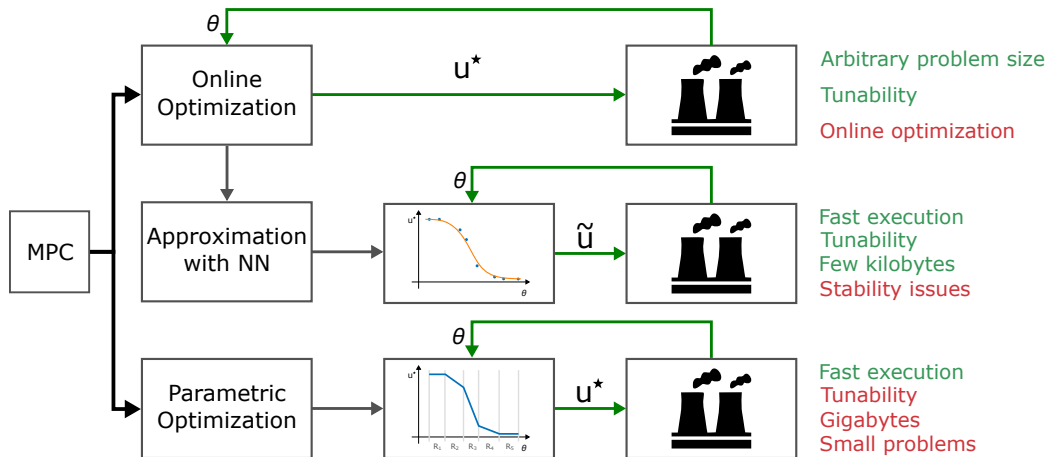
Comparison - MPC



Holy Grail of Control

- Multiple-input Multiple-output Controllers
- Optimal control action (s.t. performance, constraints, etc.)
- Fast evaluation
- Low memory footprint
- $u^* = f(\theta)$, where $f(\theta)$ is explicit function

Pros/Cons of MPC-based Control

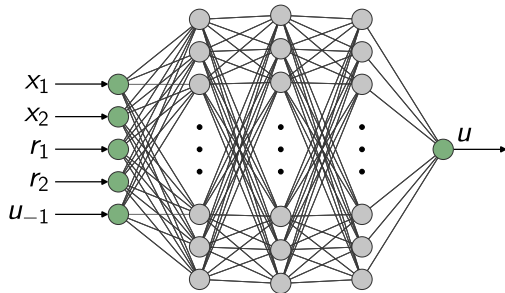
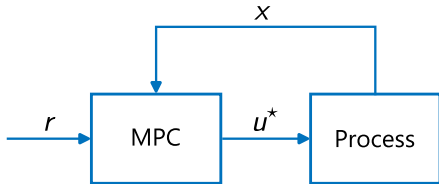


Training of Neural Network Control Law

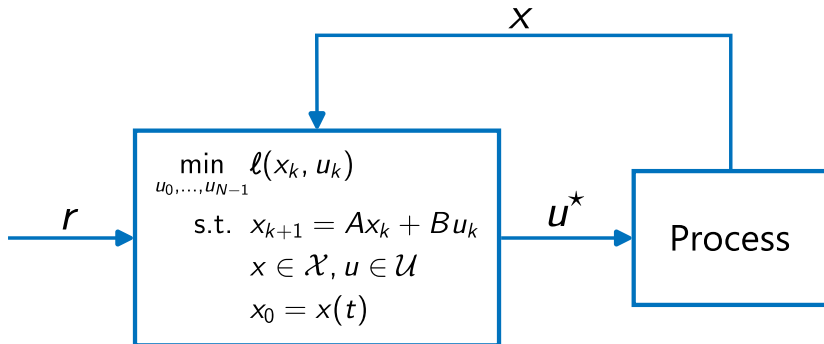
Repeatedly solve MPC for large pool of initial conditions

Train neural network
in offline mode

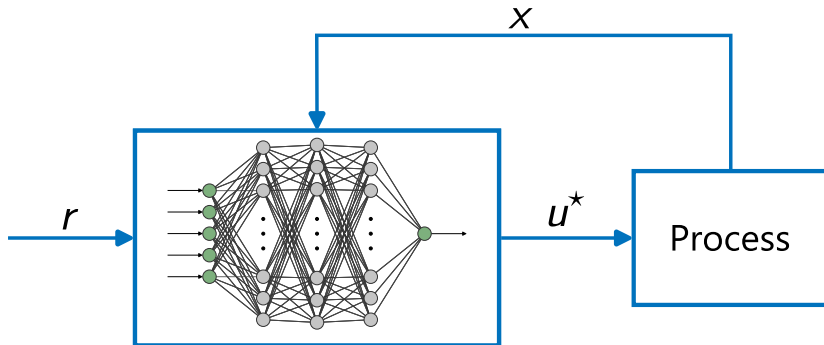
$$\min |u_{\text{NN}} - u^*|$$



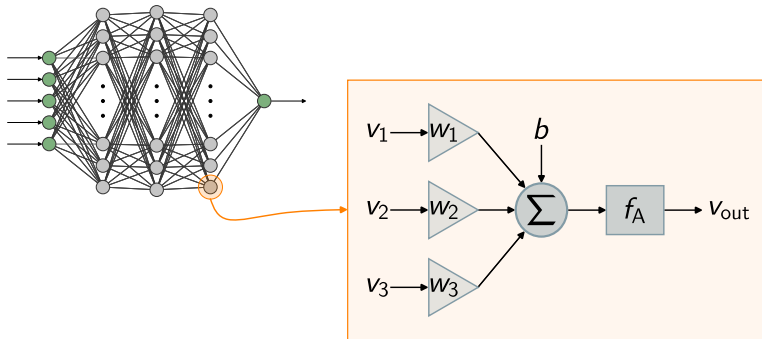
Closed-loop Arrangement with Neural Network



Closed-loop Arrangement with Neural Network

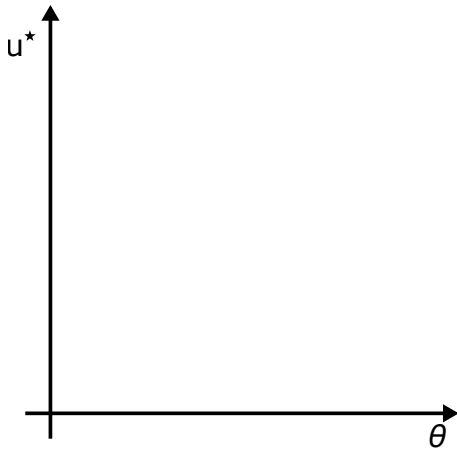


Single Neuron

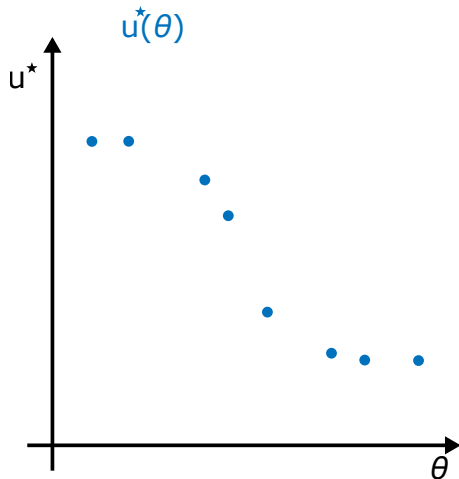


Is it a feasible approach? Can we do that?

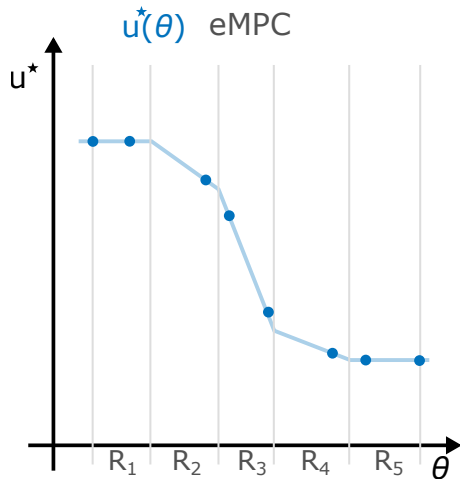
Explicit Controllers



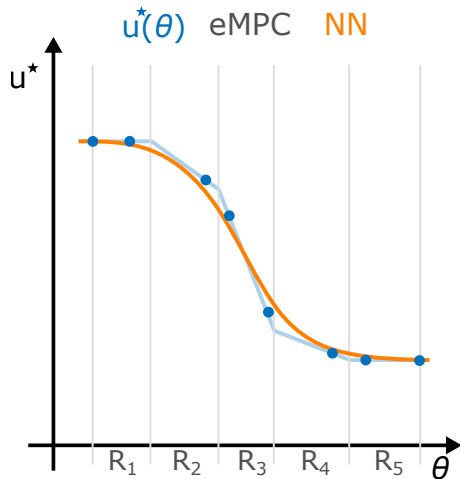
Explicit Controllers



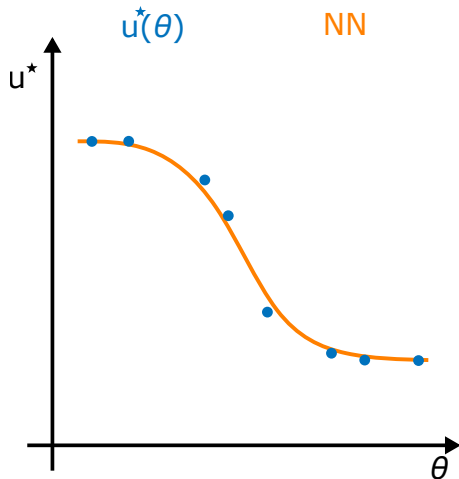
Explicit Controllers

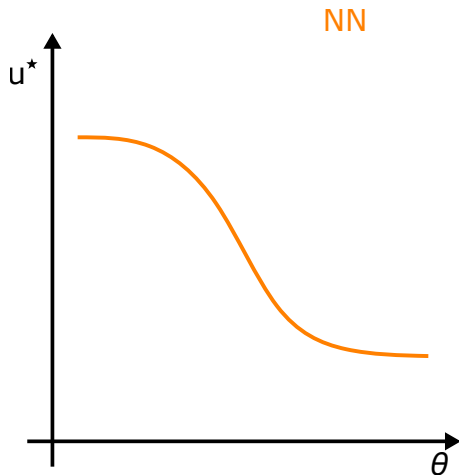


Explicit Controllers

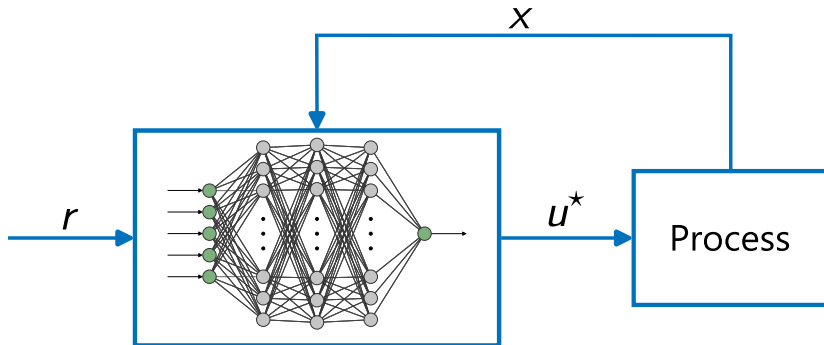


Explicit Controllers





Closed-loop Arrangement with Neural Network

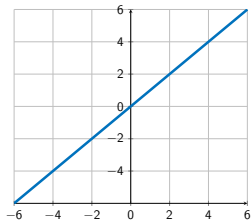


Activation Functions

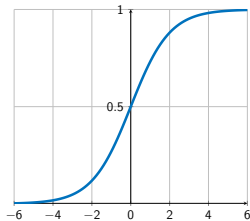
Type	Expression
Linear function	$f_A(\gamma) = \gamma$
Sigmoid function	$f_A(\gamma) = \frac{1}{1 + e^{-\gamma}}$
Hyperbolic Tangent	$f_A(\gamma) = \frac{e^{2\gamma}-1}{e^{2\gamma}+1}$
Rectified Linear Unit	$f_A(\gamma) = \max(0, \gamma)$

$$\gamma = \sum_{i=1}^{n_v} w_i \cdot v_i + b$$

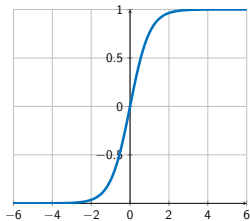
Activation Functions



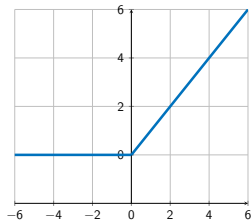
(a) Linear function



(b) Sigmoid function

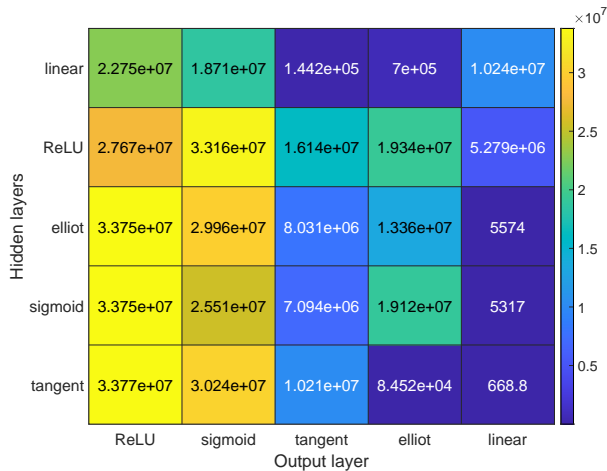


(c) Hyperbolic tangent function



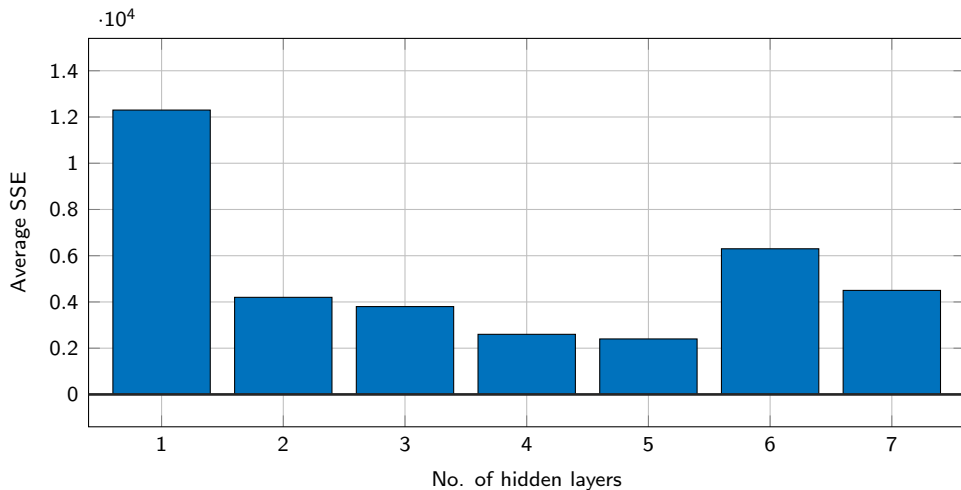
(d) ReLU function

Choice of the Structure of NN-based Controller #1



K. Kiš – M. Klaučo – A. Mészáros: *Neural Network Controllers in Chemical Technologies*. In 2020 IEEE 15th International Conference of System of Systems Engineering, IEEE, pp. 397–402, 2020.

Choice of the Structure of NN-based Controller #1



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Training of the Neural Network – NLP

$$\begin{aligned} \min_{w_i, b_i} \quad & \sum_{j=1}^M |u_{\text{NN},j} - u_j^*| \\ \text{s.t.} \quad & u_{\text{NN},j} = F(\theta_j), \quad \forall j \in \mathbb{N}_1^M \end{aligned}$$

where

$$F(\theta) = f_{A,1}\left(f_{A,2}(\dots), \dots\right)$$

objective function alternatives

$$\ell(\theta, u^*) = \frac{1}{n} (u_{\text{NN},j} - u_j^*)^2$$

solved usually by Stochastic Gradient Descent Method

Main Goals

- Concept of neural networks
- Role of neural networks as controllers
- Data generation and NN training in MATLAB
- Deployment of NN-based control laws in MATLAB

Further Reading

- K. Kiš - P. Bakaráč - M. Klaučo: Nearly Optimal Tunable MPC Strategies on Embedded Platforms. In 18th IFAC Workshop on Control Applications of Optimization, IFAC-PapersOnline, pp. 326-331, 2022, [LINK](#)
- Y. Lohr - M. Klaučo - M. Fikar - M. Mönnigmann: Machine Learning Assisted Solutions of Mixed Integer MPC on Embedded Platforms. IFAC World Congress 2020, [LINK](#)
- Sergio Lucia - Benjamin Karg: A deep learning-based approach to robust nonlinear model predictive control, 6th IFAC Conference on Nonlinear Model Predictive Control NMPC 2018, [LINK](#)

Software to Install

- Matlab
- tbxManager <https://www.tbxmanager.com/>
- YALMIP `tbxmanager install yalmip`
- (optional) MPT3 `tbxmanager install mpt mptdoc cddmex fourier glpk mex hysdel lcp yalmip sedumi espresso`
- Statistics and Machine Learning Toolbox, Deep Learning Toolbox, Control Toolbox, Optimization Toolbox

Enjoy, learn, and keep in touch

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