Embedded Deep Learning-Based Robust MPC for Fast-Sampling Atmospheric Pressure Plasma Jets Using FPGAs

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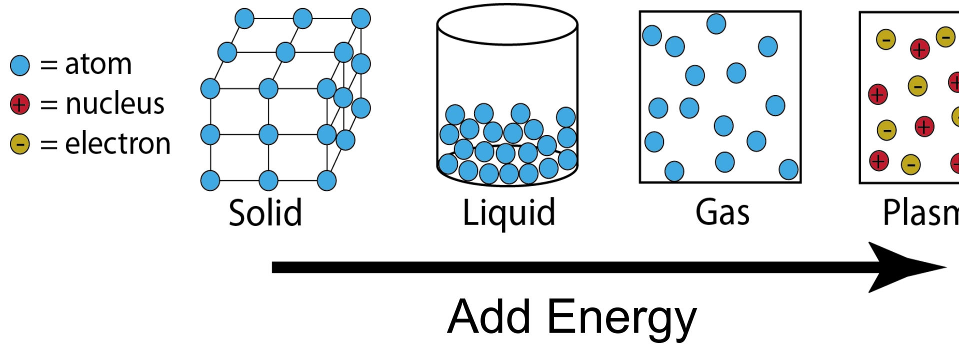
Cold Atmospheric Plasma Overview: Medical Applications



Cold Atmospheric Plasma (CAP)

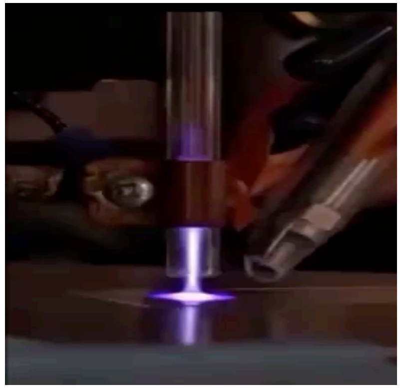
- Ionized gas ("plasma")
- Low gas temperature ("cold") compared to electron temperature

Plasma Medicine

- Highly reactive medium that offers a combination of **disinfection** and **direct stimulation** of tissues
  - Bacterial disinfection, accelerated wound healing, tumor reduction
- Current Practice:
  - No feedback control or real-time diagnostics
  - Relies on user expertise

Atmospheric Pressure Plasma Jet (APPJ)

- Device to generate CAP using quartz tube
- Portable, amenable to **point-of-care** situations ⇒ **faster** and more **accessible** treatment ⇒ improved quality of medical care



kINPen (CE), Griefswald, Germany

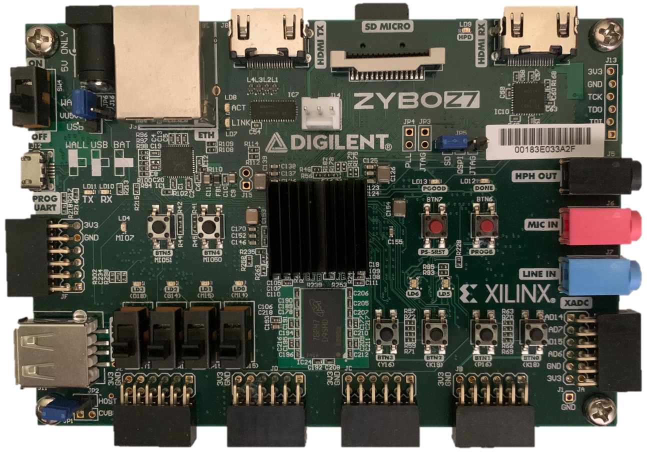
Woedtke *et al.*, 2020

APPJs for Point-of-care Devices

Challenges in APPJ Operation

- **Nonlinear** dynamics across multiple time- and length-scales
- **Fast** transport and chemistry dynamics ($\sim$ms)
- Intrinsic **variability** and **sensitivity** to exogenous disturbances
- Cumulative, non-decreasing nature of **plasma dose** delivery to complex surfaces (tissues)

Safe, **reproducible**, and **therapeutically effective** APPJ operation is an open challenge!



Aim: Enable **point-of-care plasma jets** using **resource-limited embedded** control systems

Towards Point-of-care

- Need for **advanced predictive control**
- Need for **fast-sampling** control systems
- Need for integration of **sensing** and **control** into a single device
- Need for **safety** guarantees

How to embed?

Goal: Demonstrate an **embedded** control system that results in **fast** and **safe** operation towards automated control.

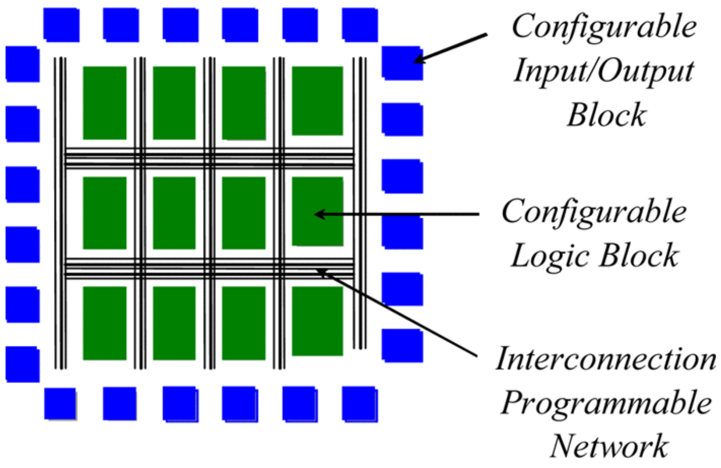
- Desirable Properties:
  - Low computational complexity
  - Small memory footprint

Explicit MPC[1]
BUT not for nonlinear model and cost functions

Approximate MPC[2,3]

Field Programmable Gate Array (FPGA)

- **Integrated circuit** (chip) composed of *configurable logic blocks* (CLBs) that are linked and **reprogrammable**



Generic Architecture of FPGA[4]

- Resource-limited Hardware ⇒ limited power, memory, computational resources
  - Cannot handle predictive control algorithms at fast sampling rates AND ensure constraint satisfaction

[1]Bemporad *et al.*, 2002
[2]Parisini and Zoppoli, 1995
[3]Karg and Lucia, 2018
[4]Monmasson and Cirstea, 2007

Problem Formulation based on *Thermal* Dose Delivery

Dose Definition

- Equivalent response of biological substrates subjected for a given amount of time to a thermal stress at a reference temperature

$$\text{CEM} = \int_0^{\tau} \underbrace{K^{(43-T(t))}}_{\text{Highly nonlinear}} d\tau$$

Integral (non-retractable)

NMPC Problem

$$V_N^\star\left(x_k, \text{CEM}_k\right) = \min_{\mathbf{U}} \left[\text{CEM}_k + \sum_{j=k}^{N} \text{CEM}\left(x_{j|k}, u_{j|k}\right) - \text{CEM}_{\text{sp}}\right]^2$$

Discretized CEM cost function

$$\begin{aligned} \text{s.t. } x_{j+1|k} &= Ax_{j|k} + Bu_{j|k} \\ y_{j|k} &= Cx_{j|k} + Du_{j|k} \\ y_{j|k} &\in \mathbb{Y}, \quad u_{j|k} \in \mathbb{U} \\ x_{0|k} &= x_k \\ \mathbf{U} &= \{u_{j|k}, \ldots, u_{N-1|k}\} \end{aligned}$$

Identified model dynamics

Input and output constraint sets

Control Law

$$\kappa_N(x; \text{CEM}) = u_0^\star$$

Sapareto and Dewey, 1984

Deep Neural Network (DNN) Approximation

Desirable properties

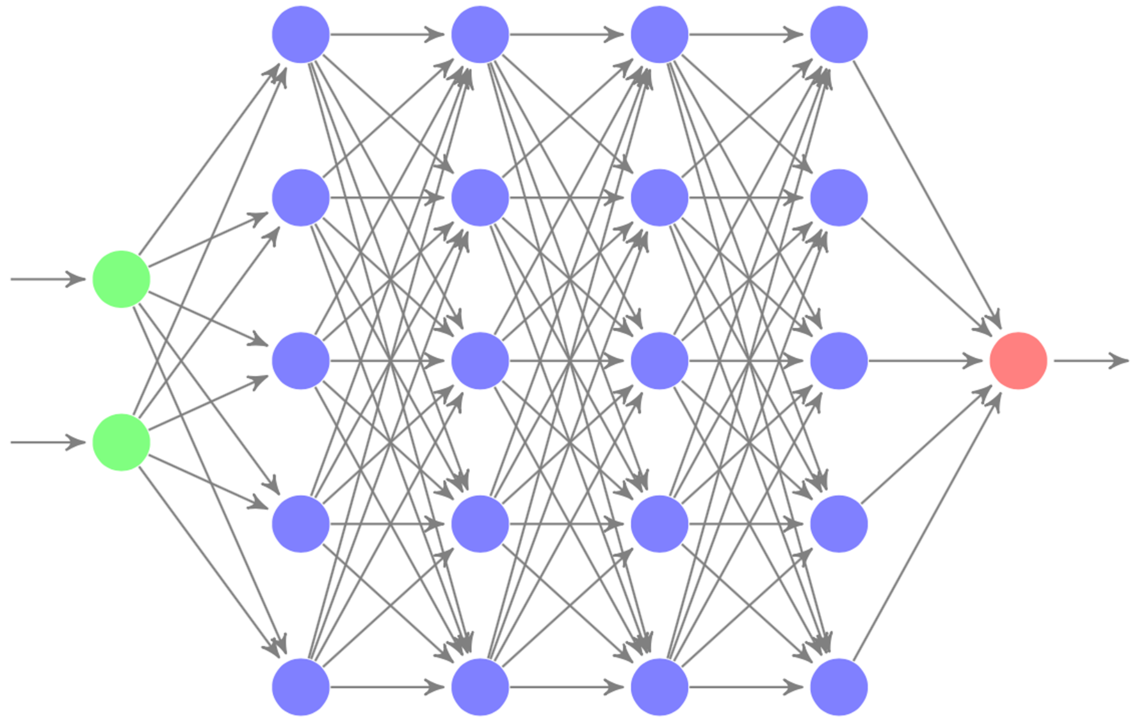
- Cheap to evaluate
- Low memory footprint

$$\underbrace{\tilde{\kappa}_N\left(x;\mathrm{CEM}\right)}_{\textbf{Explicit control law}} \approx \underbrace{\kappa_N\left(x;\mathrm{CEM}\right)}_{\textbf{MPC law (implicit)}}$$

Can be any MPC law (robust/stochastic methods)

CEM

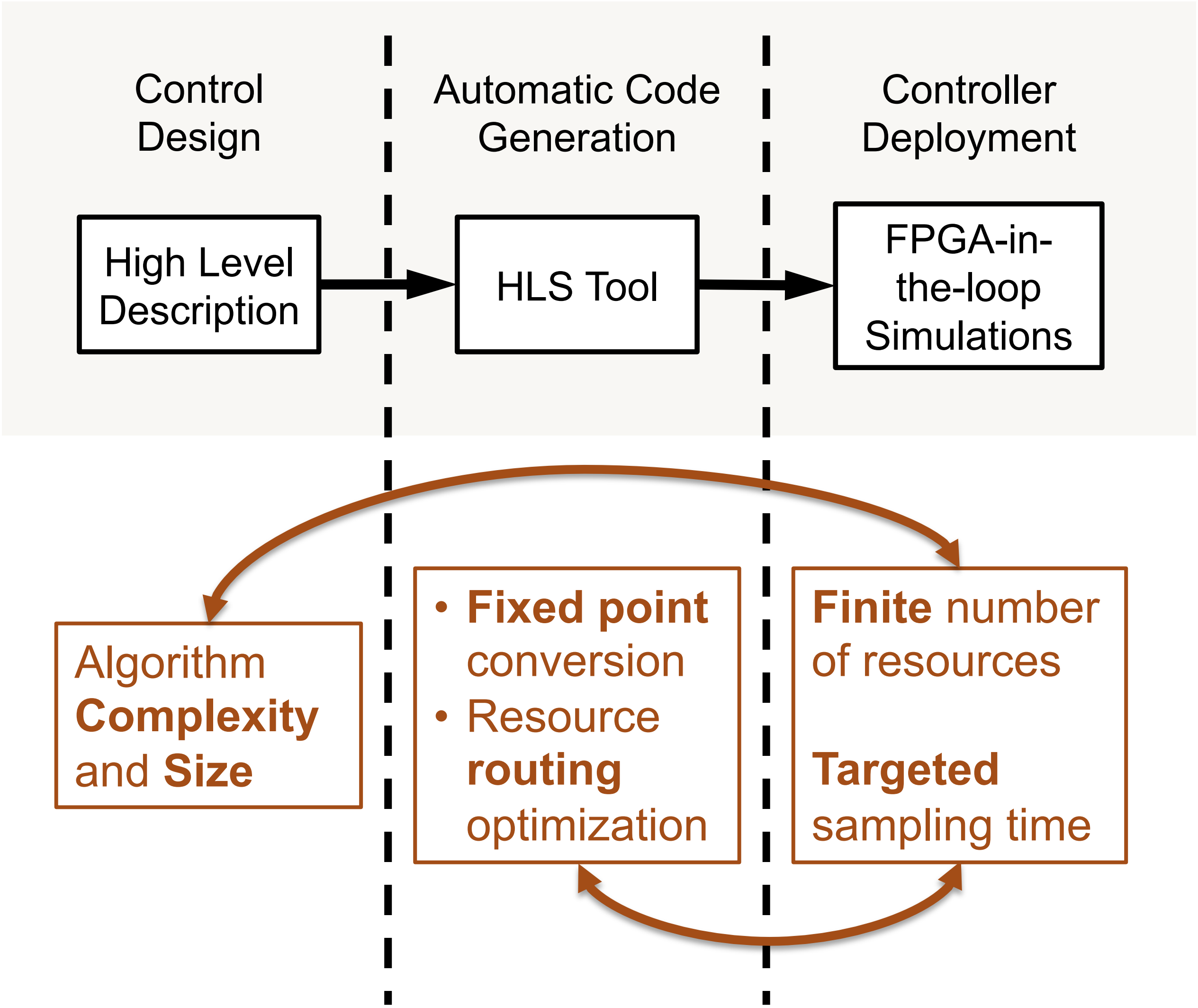
x



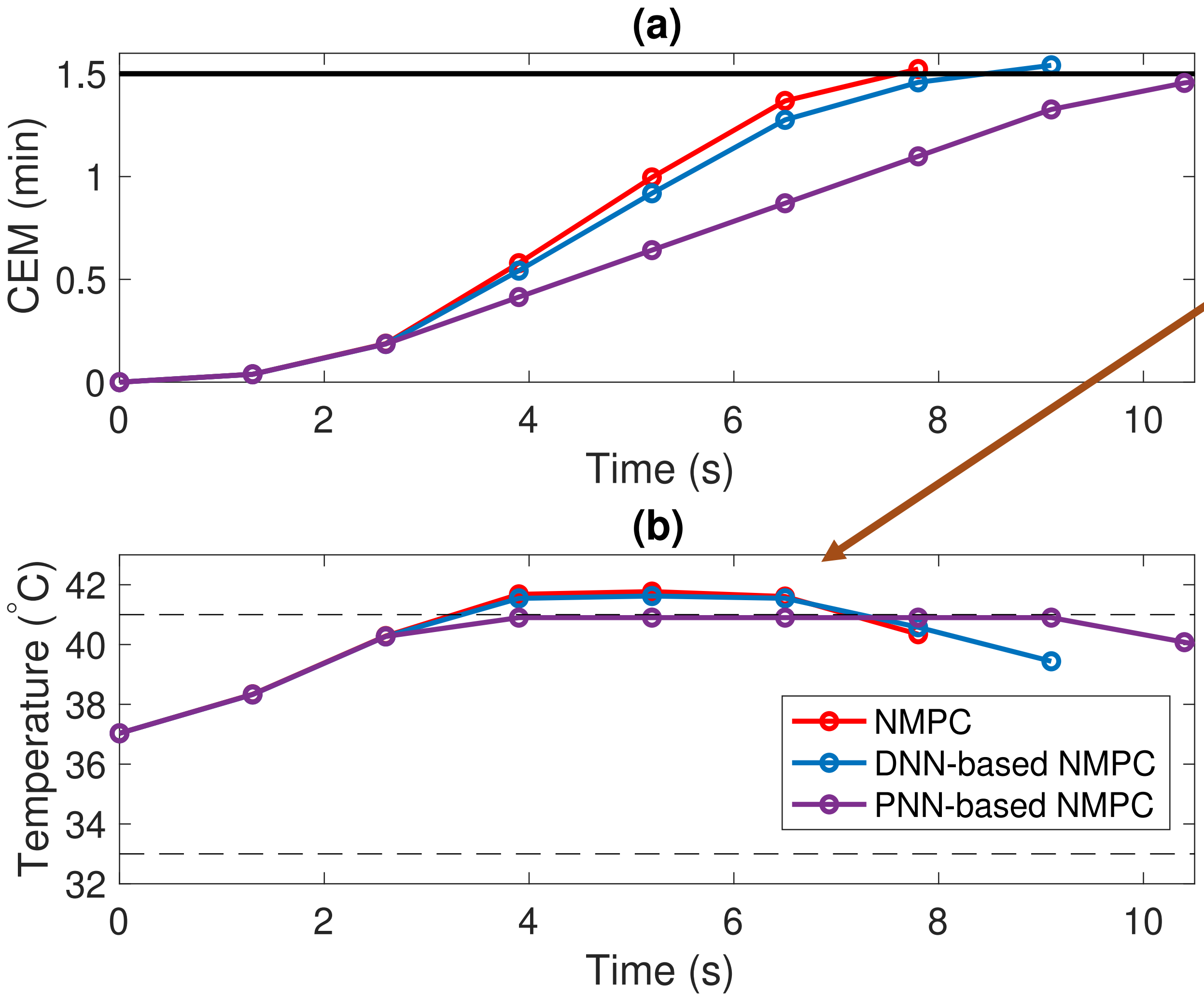
$$\overbrace{\tilde{\kappa}_N\left(x;\mathrm{CEM}\right)}^{\textbf{Replaces online solution of NMPC problem}}$$

FPGA Implementation of DNN

- Embedding requires translation to/generation of hardware level code
- High Level Synthesis (HLS)
  - Takes a high level description (e.g. MATLAB m-code, C/C++) and automatically generates hardware code
- Recall: **resource-limited**
- Design considerations ("tuning knobs") at each step affect the feasibility of final implementation.



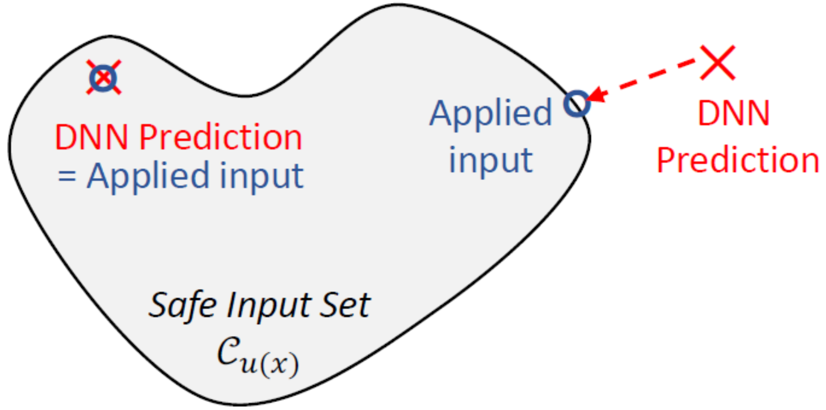
Angelo's Previous Results: Projection-based Strategy



DNN-based NMPC

- Practically indistinguishable performance from NMPC
- Constraint violation!

Projection of DNN-based control inputs onto a safe input set can eliminate constraint violations

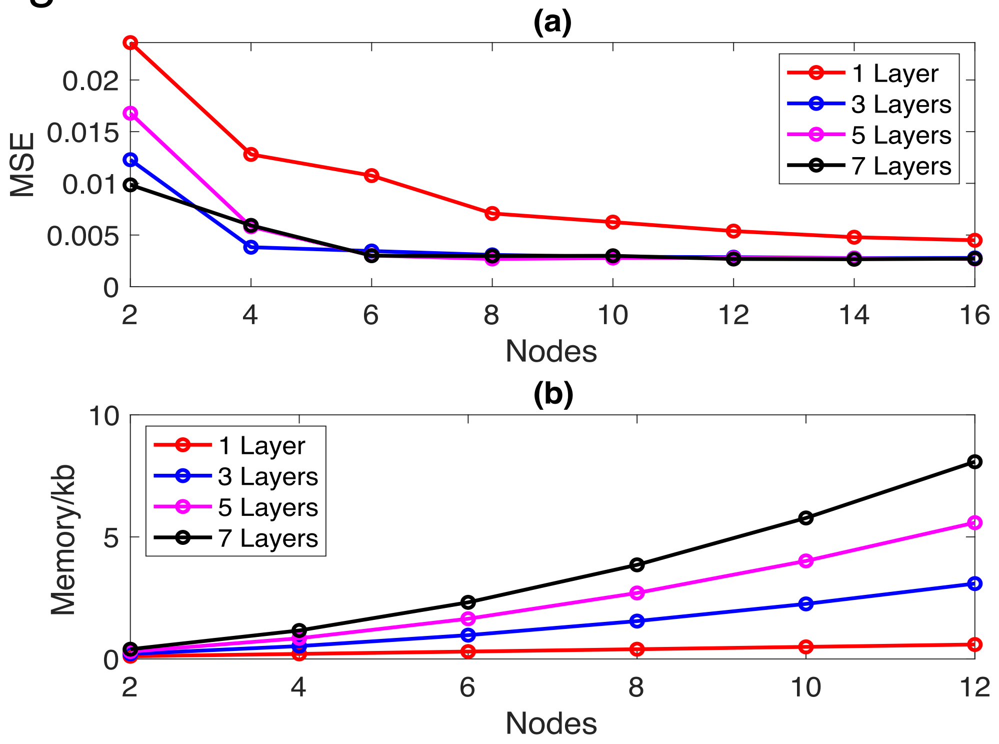


Bonzanini, Paulson, Graves, and Mesbah, 2020

Angelo’s Previous Results: Hardware Implementation Implications

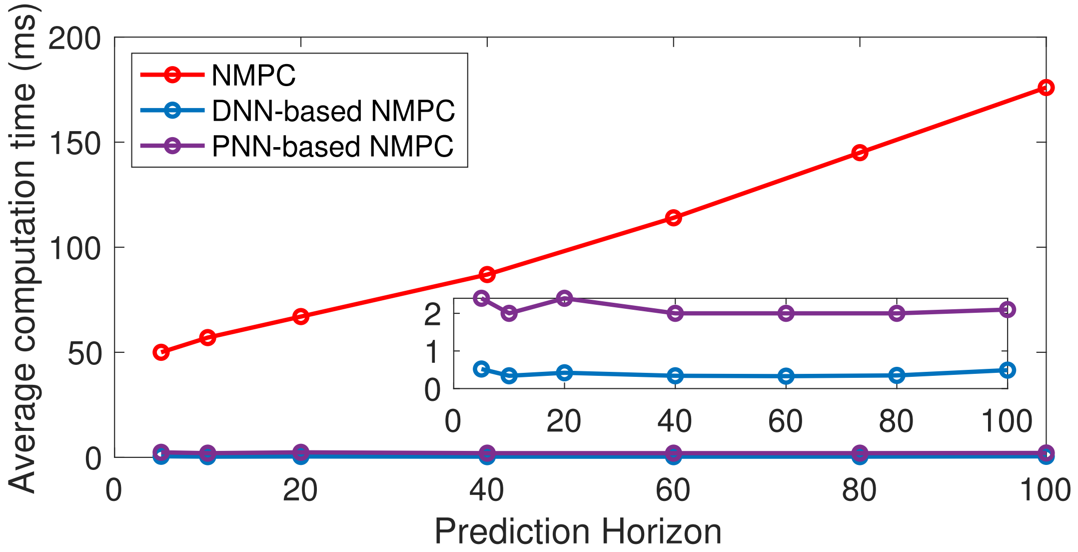
Tradeoff between low error and low memory

- Mean Squared Error (MSE) *decreases* as the **size** of DNN grows
- Memory *increases* as the **size** of the DNN grows



Computation Time

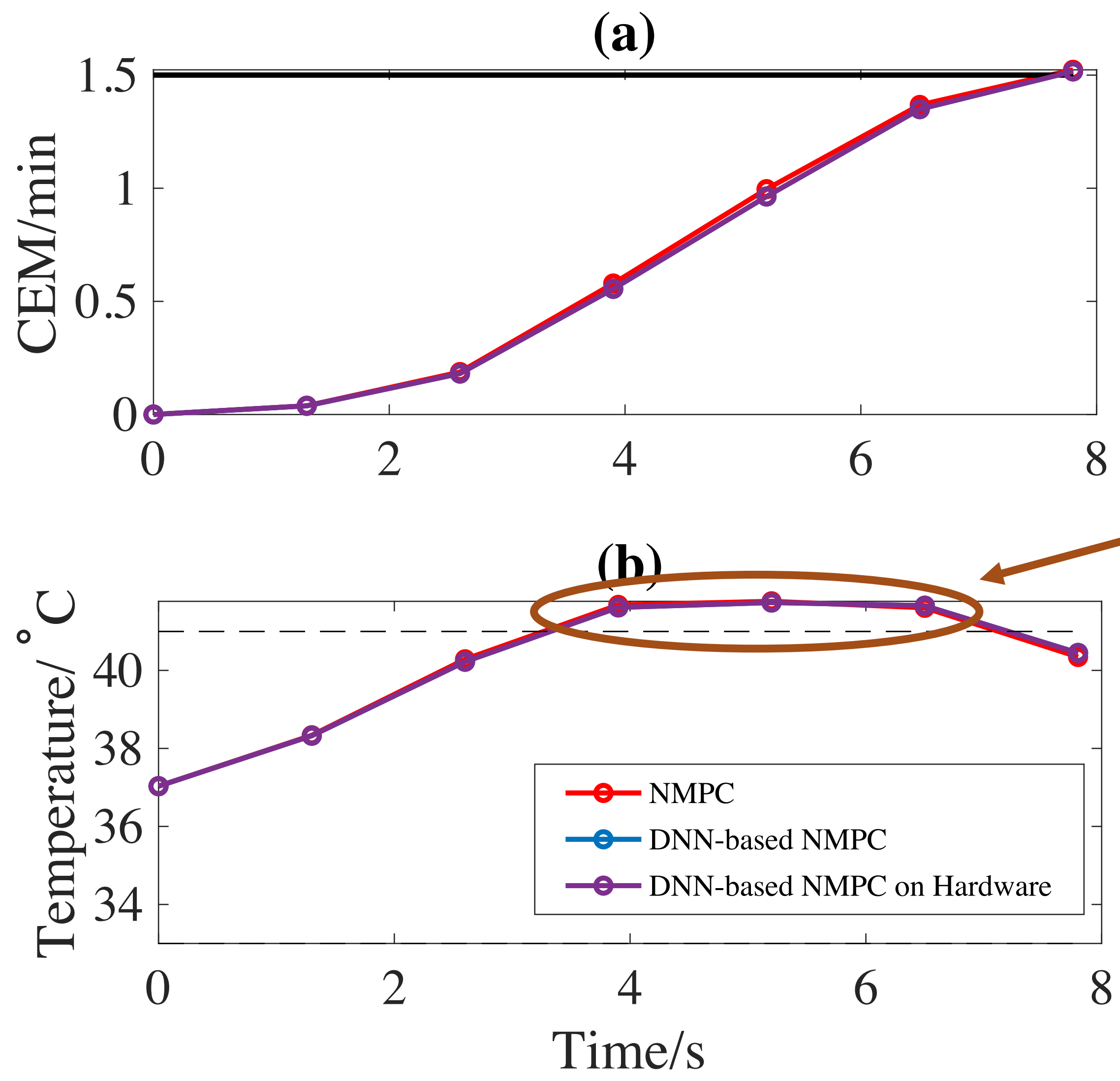
- Average reduction by a factor of 10-100



- Solving the NMPC becomes more costly as problem complexity increases
- DNN-based NMPC not affected by problem complexity
- Adding a projection step has small impact on computational cost

Bonzanini, Paulson, Graves, and Mesbah, 2020

Hardware-in-the-loop Simulations



DNN-based NMPC on Hardware

- Practically indistinguishable performance from DNN-based NMPC and NMPC

However, constraint violations still need to be addressed for the embedded context!

Next Step

- Explore methods to embed the safe input set → requires modification to the current hardware design
  - Embedding requires consideration for the storage of the safe input set

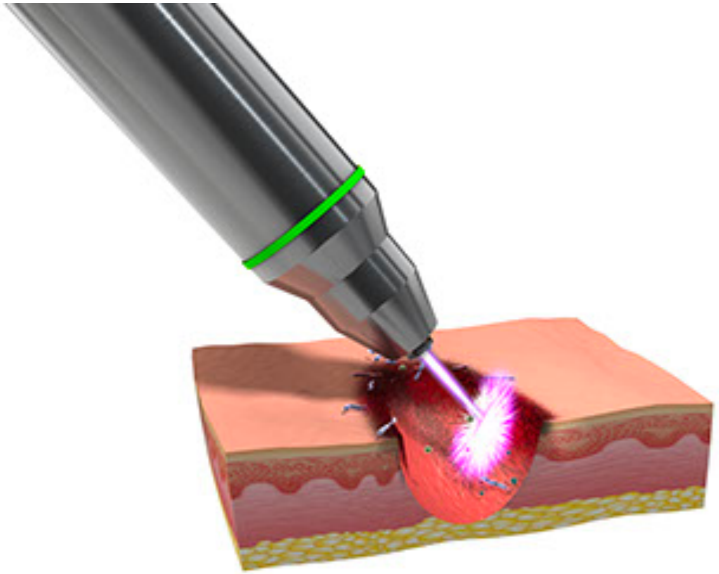
Towards Safe Embedded Control

- Approximate NMPC enables **fast** control
- Point-of-care and portable medical devices require control implementations on **resource-limited** embedded systems
- **Safe** control relies on corrections made after-the-fact

→ DNNs are a validated option

→ Hardware design involves forethought with potential for optimization

→ Safe input set projection is a demonstrated method



Beyond Plasma Medicine

- CAPs have other applications which have similar requirements (e.g. waste treatment, (bio)materials processing)
- Learning-based approximate methods applicable to any fast-sampling system

Neoplas tools, 2020

Live Chat: Nov. 19 from 8-9 AM