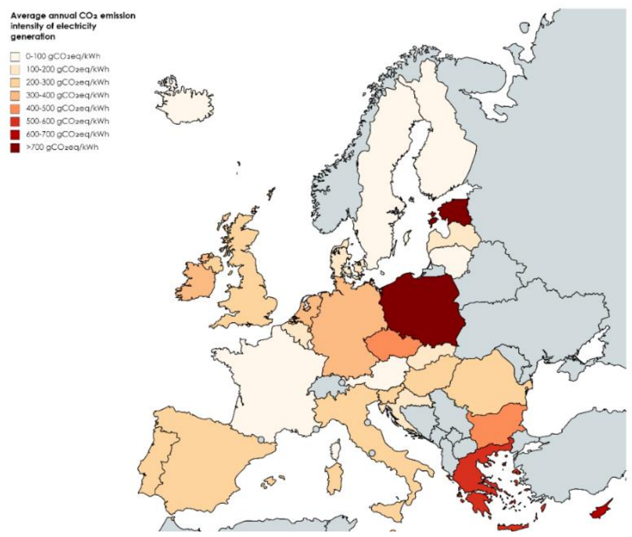
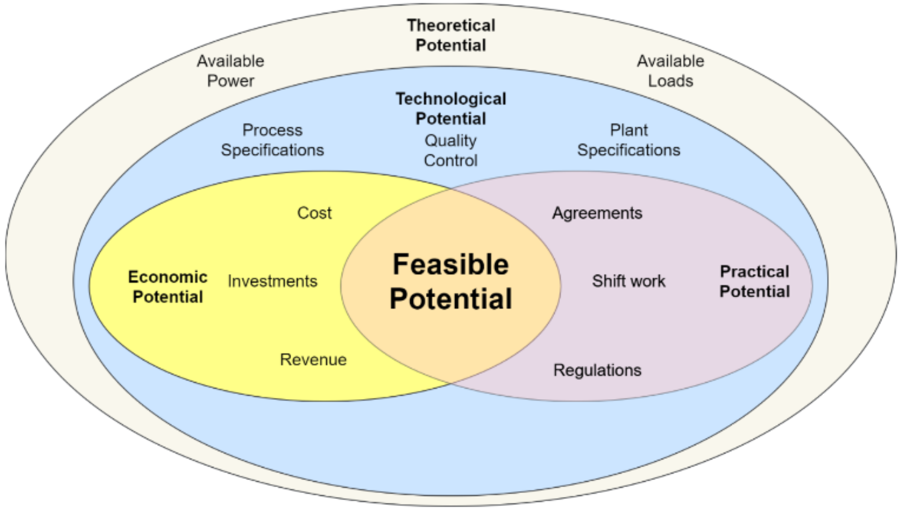
InduFlexControl: hoe flexibiliteit in energie-intensieve processen vrijstellen en vermarkten





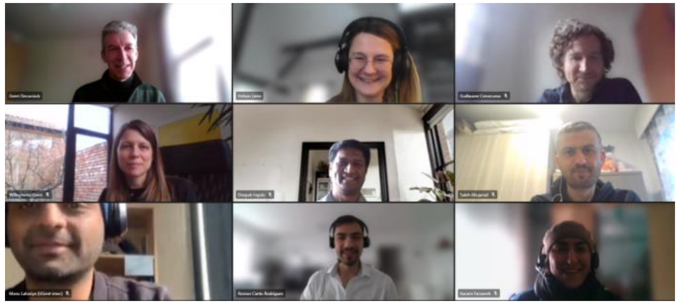
Flux50, Smart Energy Academy, 21 November 2024

prof.dr.ir. Geert Deconinck, KU Leuven ESAT-electa / KIES / EnergyVille

Control algorithms for flexibility in power-to-X and industrial processes

"4-year" Moonshot cSBO Catalisti/Flux50

- Mar 2020-Nov 2021: InduFlexControl-1
- Dec 2022-May 2025: InduFlexControl-2



KU Leuven
Faculty of Engineering Science
ELECTA – Electrical Energy Systems and Applications
The SySi– Thermal System Simulations

UGent
Faculty of Engineering Science
EELAB – Electrical Energy Laboratory
IDLab – Internet Technology and Data Science Laboratory

VITO
Department of Energy technology
AMO – Algorithms, Modelling and Optimisation
E-MARKETS – Energy Markets

industrial process

Unlock Industrial Flexibility

Investigate Control Methods

Reduce CO_2 Emissions

Redesign for Flexibility

energy ecosystem

FLANDERS INDUSTRY INNOVATION MOONSHOT

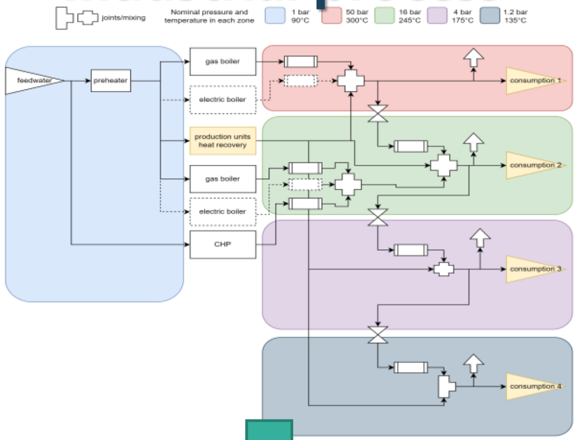
Fundamental research challenge

- integrate **model predictive control** (MPC) with data-driven **deep learning** (DL)
  - for unlocking flexibility from industrial processes
  - while incorporating constraints from industrial *process characteristics*, energy *market* design and electricity *grids*
- combines best of both worlds
  - model-based approaches for **robustness**, and model-free/data-driven techniques to deal with the **uncertainty** and complex nature of energy-intensive processes.

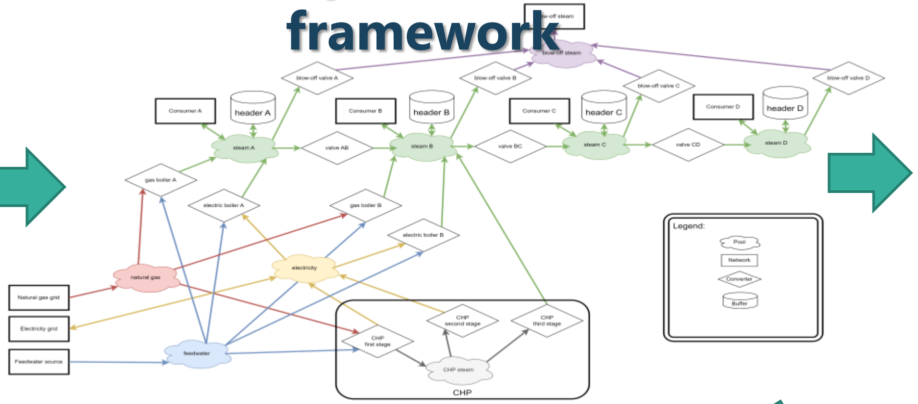
→ (re)design for flexibility of energy-intensive processes for **reduced costs and emissions**

Approach

Industrial process



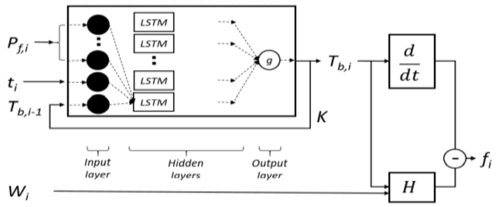
Flex quantification framework



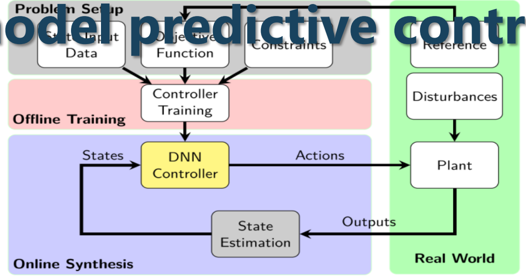
Bids generation and markets

Elementary Order	Constraint type
price (€/MWh)	
quantity (MWh)	exclusive
market zone	implication
sense (buy/sell)	linked
timestep (h)	linked order ratio
acceptance	minimum ratio
ratio	pro-rata

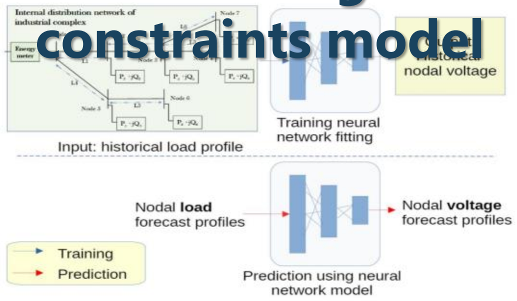
Physics-inspired NN dynamic model



DNN model predictive control



Industrial grid constraints model



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Result example 1: Multi-market integration for industrial flexibility

Industry Sub-Model

Processes Constraints/Parameters

PR1 PR2 ··· PRn

Market Sub-Model

Market Constraints/ Parameters

MK1 MK2 ··· MKn

CO_2 Sub-Model

Strategies to reduce CO_2 emissions

CS1 CS2 ··· CSn

Bidding Strategy Model: Decision Model of the Industrial Player

Benefit to Industrial Process (extra income, lower cost)

Market Results (purchased flex, prices)

Environment Results (CO_2 reduction)

Uncertainty in market prices (day-ahead prices, balancing prices, **imbalance settlement prices**, products prices)

Result example 1: Multi-market integration for industrial flexibility


InduFlexControl-2

Control algorithms for flexibility in power-to-X and industrial processes

D3.1- Multi-Platform valorisation of flexibility in composite industrial processes

July 26, 2024

Consortium:

Financial support:

Objective

What is most economical and carbon-efficient way to leverage industrial flex in energy and balancing markets?

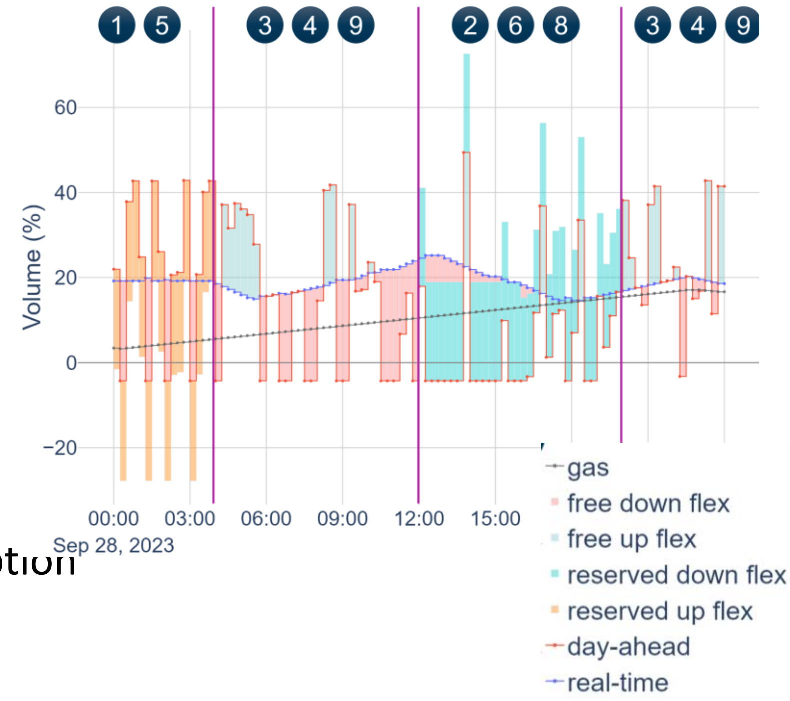
Key Findings

aFRR: Free bids provided highest profitability;
decisions can be taken closer to real-time when more information is available.

mFRR: Reservations dominated with no activation;
provision of mFRR leads to losses in most quarters.

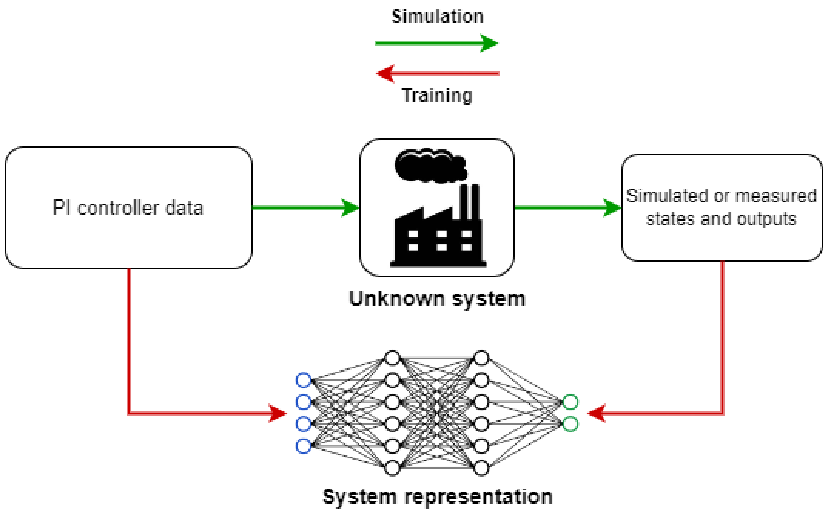
Imbalance: Significant gains possible by optimizing real-time consumption and generation adjustments; highly profitable but assumes “perfect foresight”

CO_2 reduction: Both indirect and direct strategies reduced emissions, with gas consumption lowered by 11% in direct reduction scenarios.

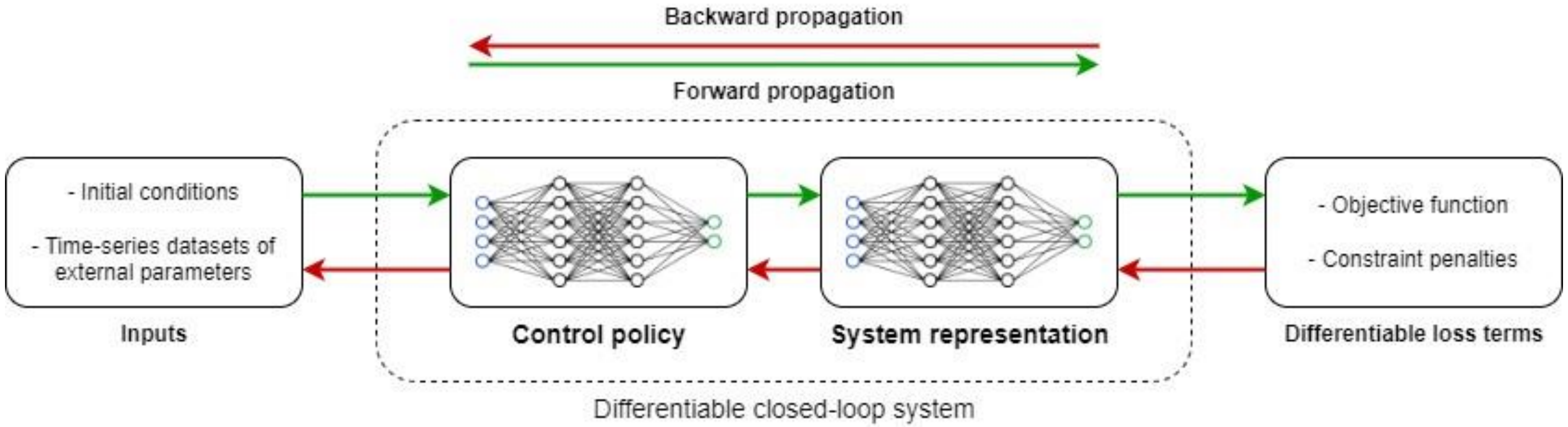


Result example 2: from white-box to data and combining MPC with ML

System identification



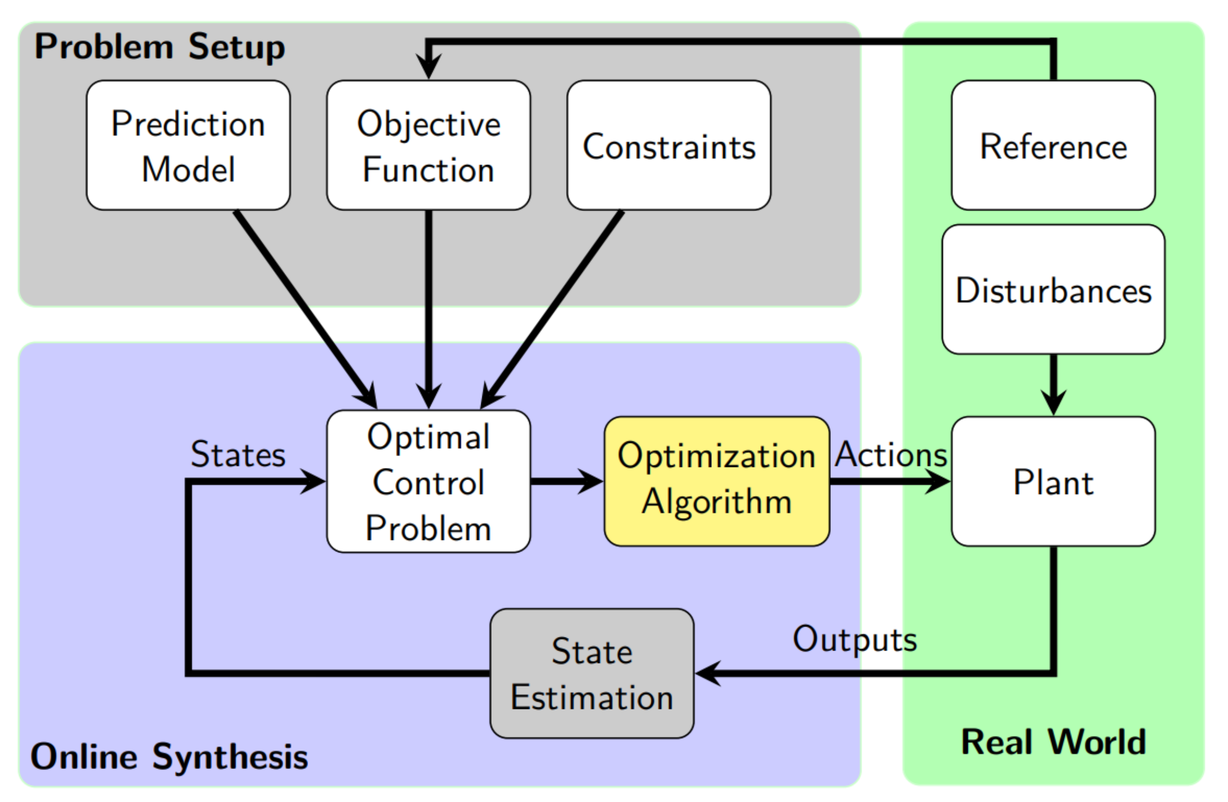
Control policy training



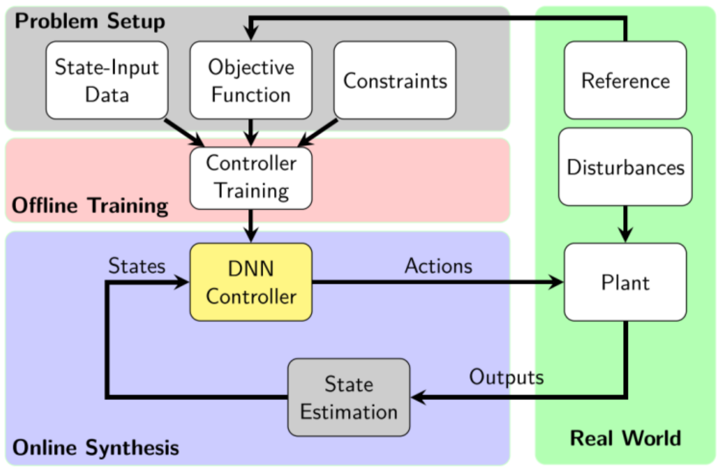
Ján Drgoňa, Karol Kiš, Aaron Tuor, Draguna Vrabie, Martin Klaučo, Differentiable predictive control: Deep learning alternative to explicit model predictive control for unknown nonlinear systems, Journal of Process Control, Volume 116, 2022, Pages 80-92

Implement fast and robust model predictive control

- Strengths of MPC
  - Control → solve optimisation
  - Nonlinear dynamics
  - Input constraints
  - General objective functions
- Weakness
  - Computationally demanding
  - Online optimisation
  - No explicit formulation for nonlinear systems



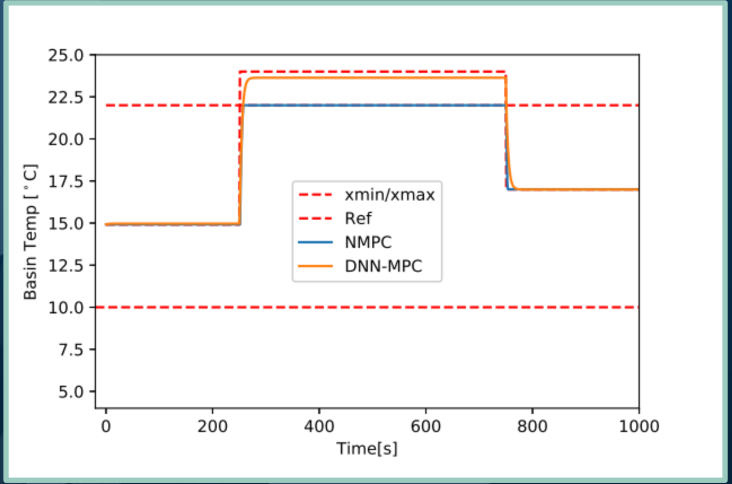
Neural Network based approximate nonlinear MPC



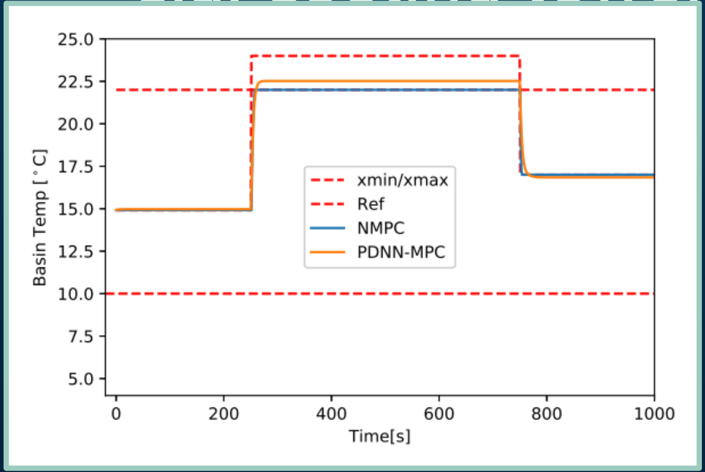
- Deep neural network MPC
  - Offline training based on observations
  - Learn optimum control policy
  - Different methods for <u>constraints handling</u>

e.g. cooling tower

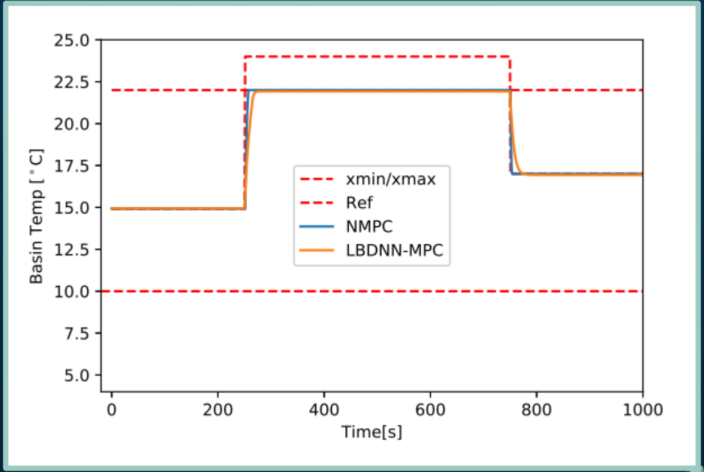
Log Barrier



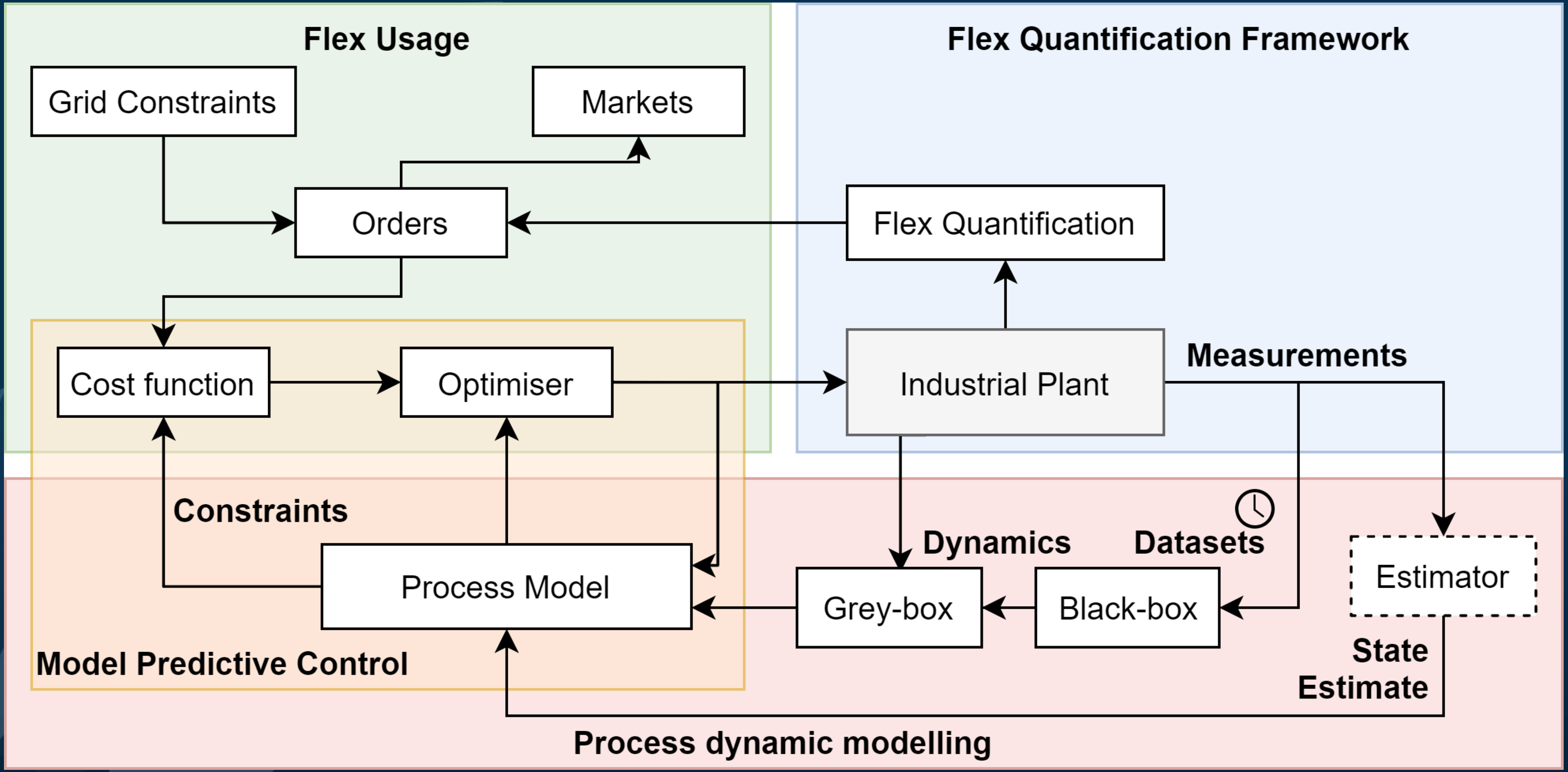
No Constraints



Penalty



Closing the loop



Valorisation potential

- InduFlexControl can
  - quantify and design flexibility models for your target processes
  - develop data-driven representations of your processes and benchmark them with existing models
  - evaluate the use of your processes’ flexibility in relevant energy markets and specific grid situations
  - design model predictive control methods for exploiting the flexibility of your processes

Reduce your CO_2 emissions by using the underlying flexibility of your processes

Highlights – publication output

[J1] C. Manna, M. Lahariya, F. Karami, and C. Develder, “A data-driven optimization framework for industrial demand-side flexibility,” Energy, vol. 278, p. 127737, Sep. 2023, doi: 10.1016/J.ENERGY.2023.127737.

[J2] M. Lahariya, F. Karami, C. Develder, and G. Crevecoeur, “Physics-Informed LSTM Network for Flexibility Identification in Evaporative Cooling System,” IEEE Trans. Ind. Informatics, vol. 19, no. 2, pp. 1484–1494, Feb. 2023, doi: 10.1109/TII.2022.3173897.

[J3] R. Cantu Rodriguez, E. J. Palacios-Garcia, and G. Deconinck, “Redesign for flexibility through electrification: Multi-objective optimization of the operation of a multi-energy industrial steam network,” Appl. Energy, vol. 362, p. 122981, May 2024, doi: 10.1016/J.APENERGY.2024.122981.

[B1] R. Cantu-Rodriguez, E. J. Palacios-García, and G. Deconinck, “Modelling and Optimal Scheduling of Flexibility in Energy-Intensive Industry,” in Industrial Demand Response: Methods, best practices, case studies, and applications, H. Haes Alhelou, A. Moreno-Muñoz, and P. Siano, Eds. Institution of Engineering and Technology (IET), 2022, pp. 209–240.

+ many conference publications

Contact information

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