

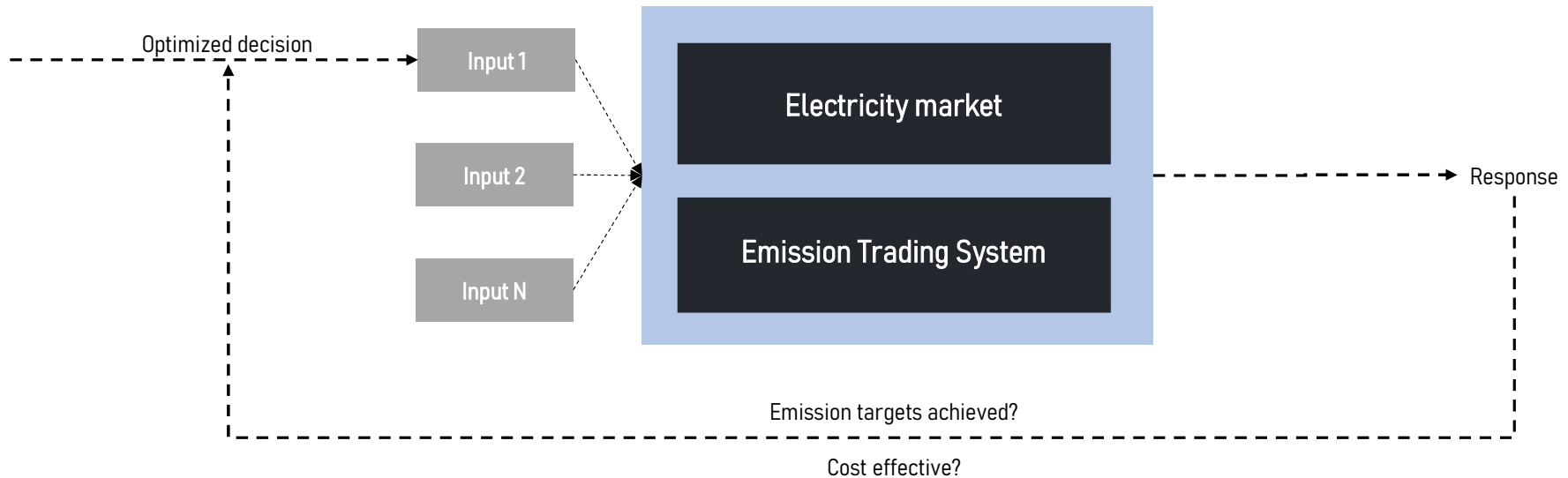
Capturing Electricity Market Dynamics in the Optimal Trading of Strategic Agents using Neural Network Constrained Optimization

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**Mihaly Dolanyi, Kenneth Bruninx,
Jean-Francois Toubreau & Erik Delarue**

**WP link: <https://www.mech.kuleuven.be/esim>
mihaly.dolanyi@kuleuven.be**

Motivation



How to differ EM & ETS inputs to achieve desired emission levels in a cost effective way?

Electricity markets differ from common stock exchanges as they are governed by known physical and economic equations.

How to exploit these characteristics to achieve an optimal response w.r.t. a given decision problem?

Traditional MPEC approach and the proposed MPNNC

MPEC:

- Represents the LL via the optimality conditions of the “believed” underlying optimization problem
- The optimization problem is typically far from reality.
- It is difficult to solve the resulting problem to optimality.

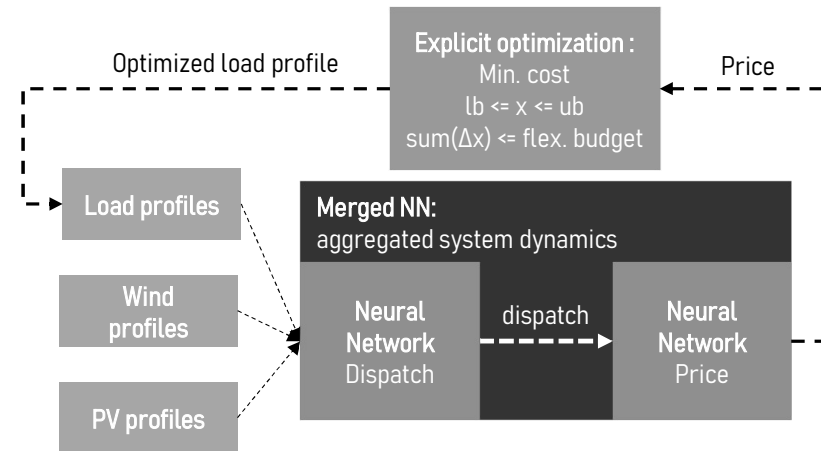
MPNNC:

- Characterize the LL via an input convex neural network* that finds mapping between inputs and resulting market prices.
- Flexibility to be deployed where the underlying NN has sufficient forecasting power.
- The solution is biased by the accuracy of the NN.

**B. Amos, L. Xu, and J. Z. Kolter, “Input convex neural networks,” International Conference on Machine Learning. PMLR, 2017, pp. 146–155..*

The solution method

1. Train the first NN to find the optimal dispatch of the generators, given the inputs.
2. Train the second NN to find the resulting prices given the forecasted dispatch.
3. Chain the NNs, such that they represent the mapping between market prices and market inputs.
4. Formulate the UL optimization problem with given constraints.
5. Use an applicable second-order optimization method* to decide on the optimal inputs.

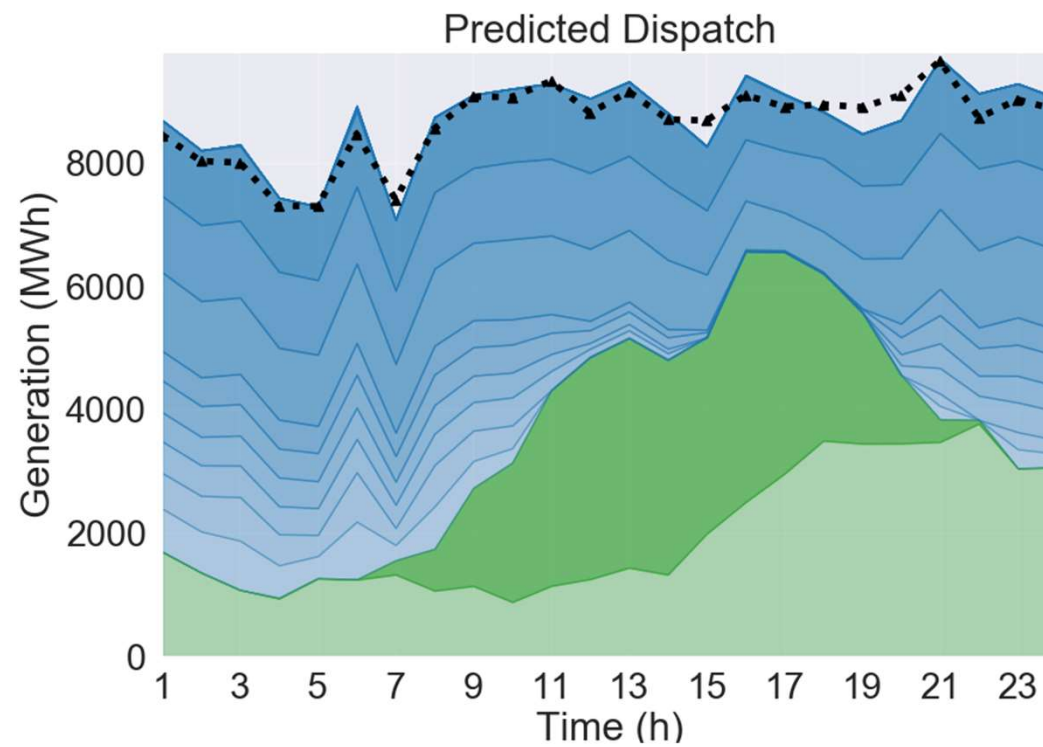


*D. Kraft et al., "A software package for sequential quadratic programming," 1988.

STEP I:

Training the NNs to predict the environment's behaviour

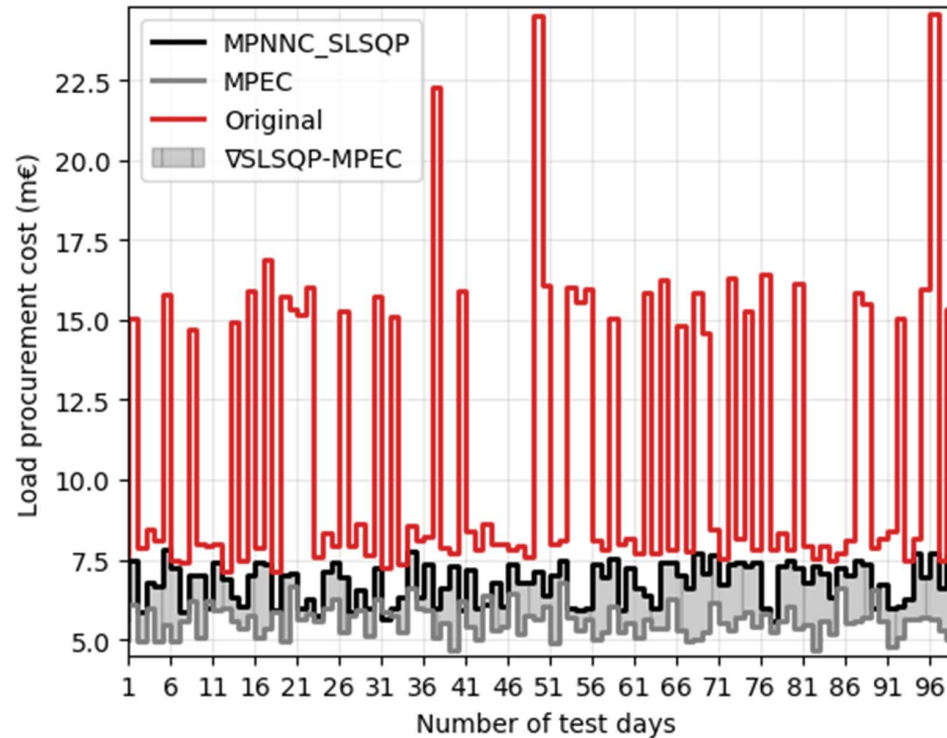
Learning the economics dispatch model



lr = 0.001
optimizer = ADAM
#training days = 400
#iterations = 50

STEP II: Optimal bidding, given the flexibility constraints and the chained NN

Comparing the NN-based optimization to bi-level programming



	Original	MPNNC	MPEC
Sum Time (s)	-	52	1196
Avg. Time (s)	-	0.5	12
Sum Cost (€)	1.09e9	6.76e8	5.58e8

Conclusions



An alternative approach to bi-level programming has been proposed for optimally stimulating electricity markets.

The presented NN based optimization method is more flexible and has better potential for real life deployment.

Through the optimal bidding of the demand agent it was shown that the MPNNC results are getting reasonably close to the MPEC.

The limitation for applicability lies in how well the NN can learn the underlying system dynamics.

Thank you for your attention!
mihaly.dolanyi@kuleuven.be