IMPERIAL

AI Based Electricity Markets

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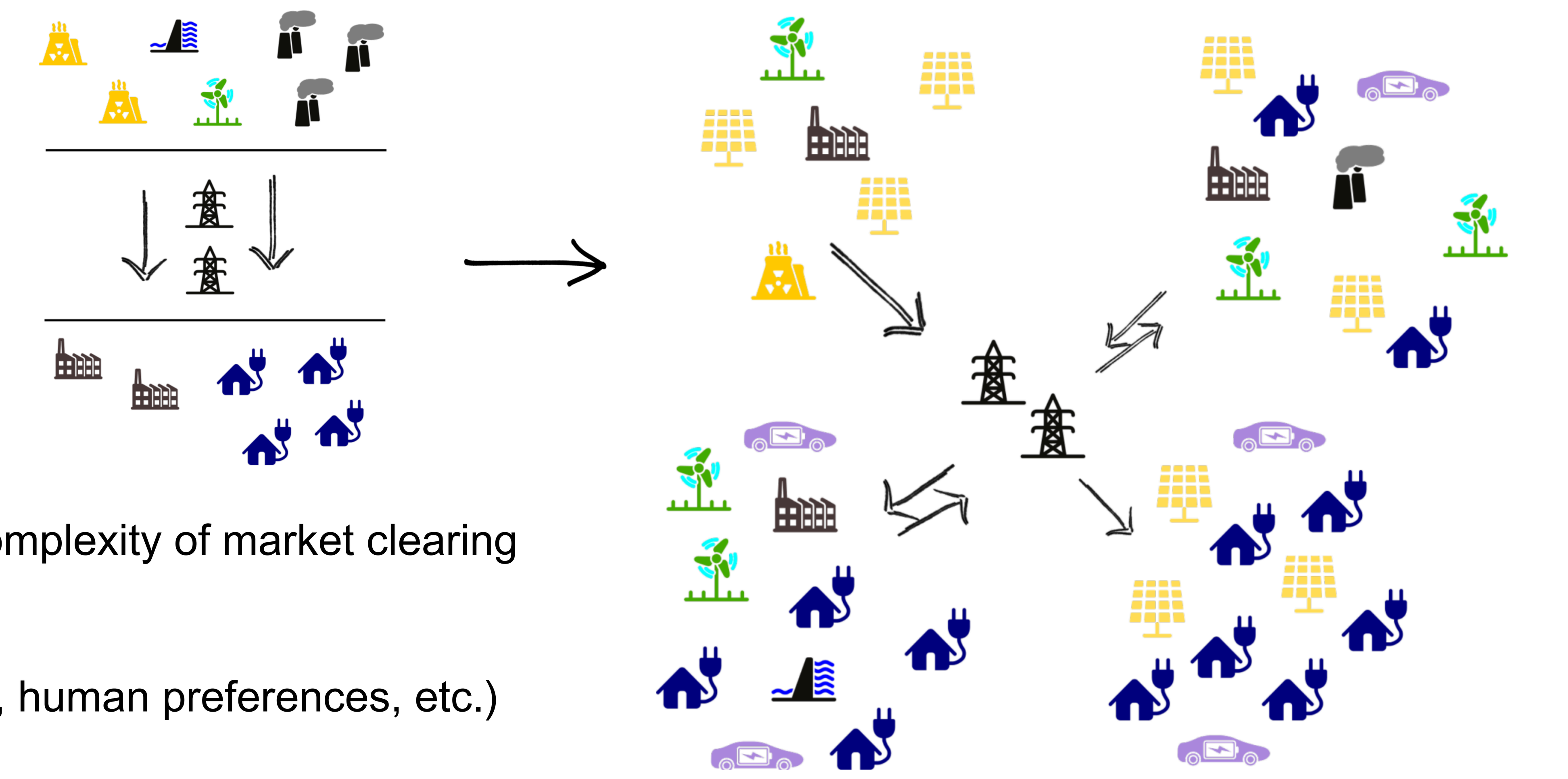
Ambition and Objectives

Linear Programming (LP) is at the core of electricity markets (clearing), allowing to jointly solve **resource allocation** and **pricing** problems.

Our aim is to replace that LP with an AI.



Motivation Points

1. High availability of contextual data
2. Decentralisation, as well as increase in dimensionality and complexity of market clearing
3. High one-off cost to train, but very cheap to use afterwards
4. Flexibility to accommodate important future aspects (fairness, human preferences, etc.)

Methodology

Original LP problem

$$\begin{cases} \min_{\mathbf{x}} & \mathbf{D}^T\mathbf{x} \\ \text{s.t.} & \mathbf{A}\mathbf{x} - \mathbf{b} \le 0 \end{cases}$$

KKT conditions

$$\mathbf{D} + \mathbf{A}^T\mathbf{u} = 0$$
$$\mathbf{u}^T(\mathbf{A}\mathbf{x} - \mathbf{b}) = 0$$
$$\mathbf{A}\mathbf{x} - \mathbf{b} \le 0$$
$$\mathbf{u}^T \ge 0$$

→

Corresponding ODE system

$$\frac{d\mathbf{y}}{dt} = \Phi(\mathbf{y}) = \begin{bmatrix} -\left(\mathbf{D} + \mathbf{A}^T(\mathbf{u} + \mathbf{A}\mathbf{x} - \mathbf{b})^+\right) \\ (\mathbf{u} + \mathbf{A}\mathbf{x} - \mathbf{b})^+ - \mathbf{u} \end{bmatrix}$$

Initial conditions

$$\mathbf{y}(0) = \mathbf{0}$$

Time range

$$t \in [0, T]$$

→

Approximate state solution

$$\hat{y}(t, \mathbf{b}, \mathbf{D}; \mathbf{w}) = \left(1 - e^{-t}\right)\mathrm{NN}(t, \mathbf{b}, \mathbf{D}; \mathbf{w})$$

Approximate solution to the KKT conditions

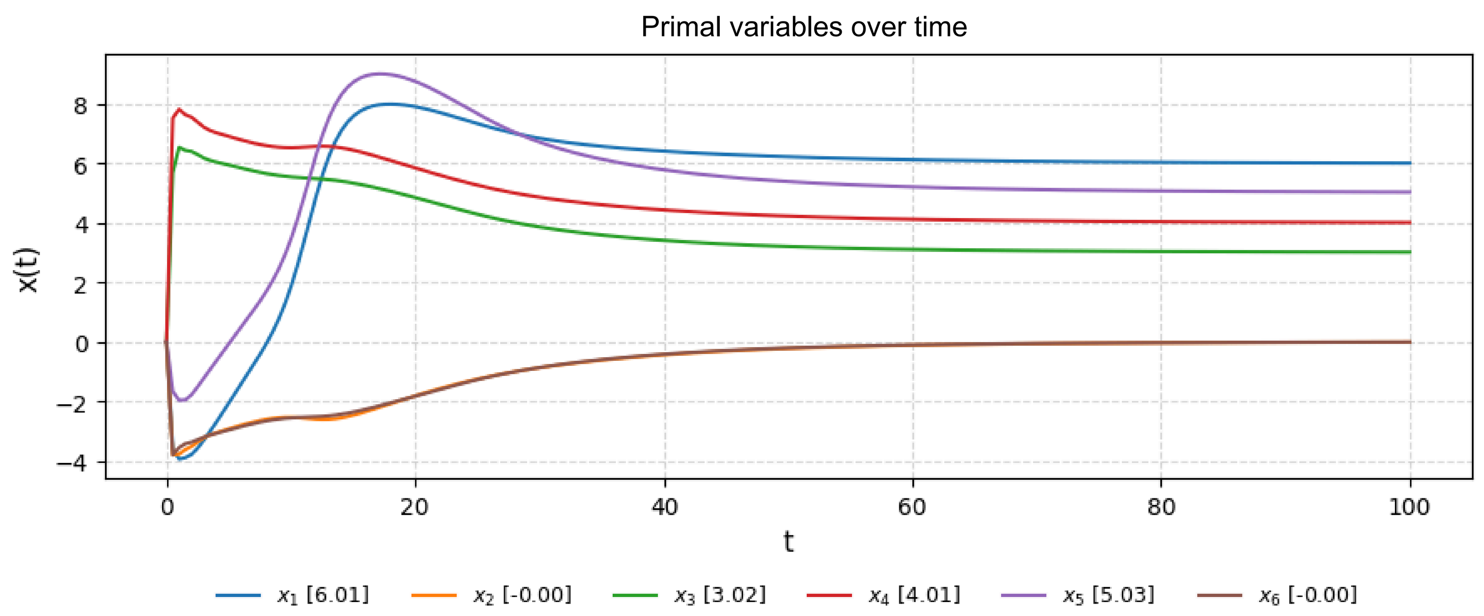
$$\hat{y}(T, \mathbf{b}, \mathbf{D}; \mathbf{w}) = \left(1 - e^{-T}\right)\mathrm{NN}(T, \mathbf{b}, \mathbf{D}; \mathbf{w})$$

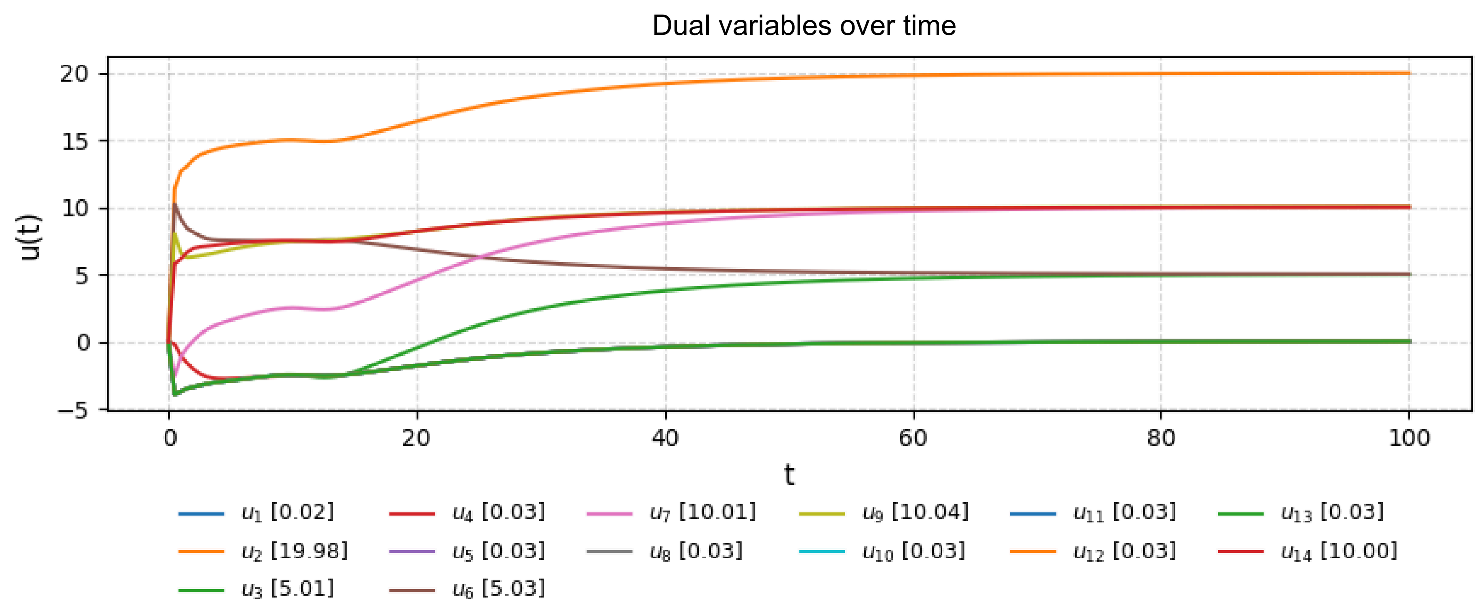
Example Neural Network approximating an LP problem

$$\max\ 30x_1 + 20x_2 + 10x_3 - 15x_4 - 25x_5 - 10x_6$$

$$\text{s.t.}\quad x_1 + x_2 + x_3 = x_4 + x_5 + x_6$$

$$0 \le x_1 \le 6 \qquad 0 \le x_4 \le 4$$
$$0 \le x_2 \le 5 \qquad 0 \le x_5 \le 7$$
$$0 \le x_3 \le 3 \qquad 0 \le x_6 \le 2$$

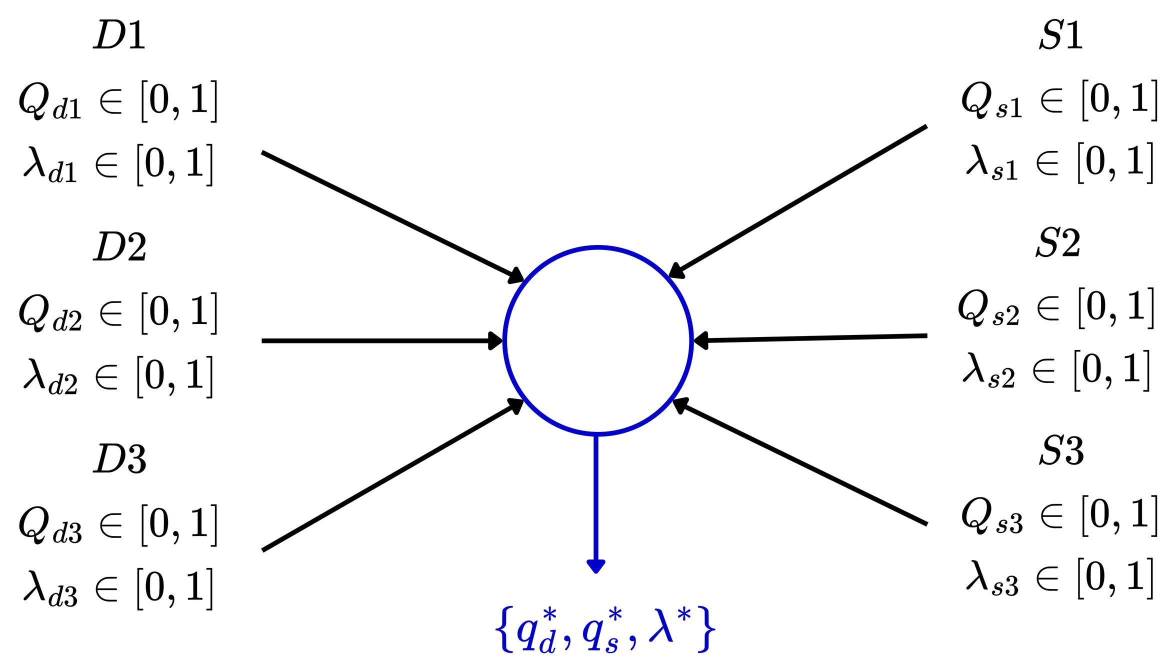


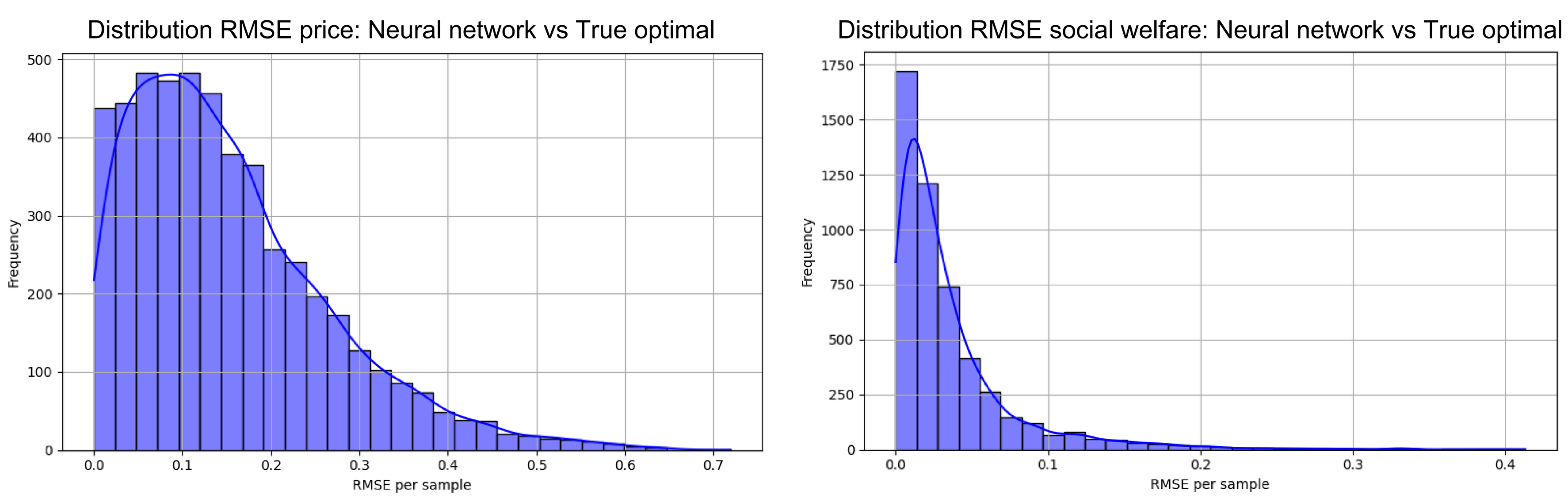


- Primal and dual trajectories converge smoothly, especially in low dimensions.
- Despite near-optimal solutions, constraint violations may occur, necessitating a feasibility projection step to ensure valid outputs.

Example Neural Network generalisation

A neural network was trained on randomly sampled single-node electricity markets (3 supply and 3 demand bids, with prices and quantities in [0,1]), and evaluated on 5,000 unseen market instances, using the true optimal solutions to generate error distributions for price and social welfare.





- Social welfare RMSE is tightly peaked near zero, suggesting strong generalisation.
- Price RMSE distribution is concentrated around 0.1 with a long tail, suggesting overall accuracy but occasional large errors likely due to active set changes or non-smooth transitions in the dual solution space near constraint boundaries.

Ongoing Work and Perspective

Better restoration of feasibility

Improving accuracy

Focus on scalability

Wu, D., & Lisser, A. (2023). A deep learning approach for solving linear programming problems. Neurocomputing, 520, 15-24 https://doi.org/10.1016/j.neucom.2022.11.053