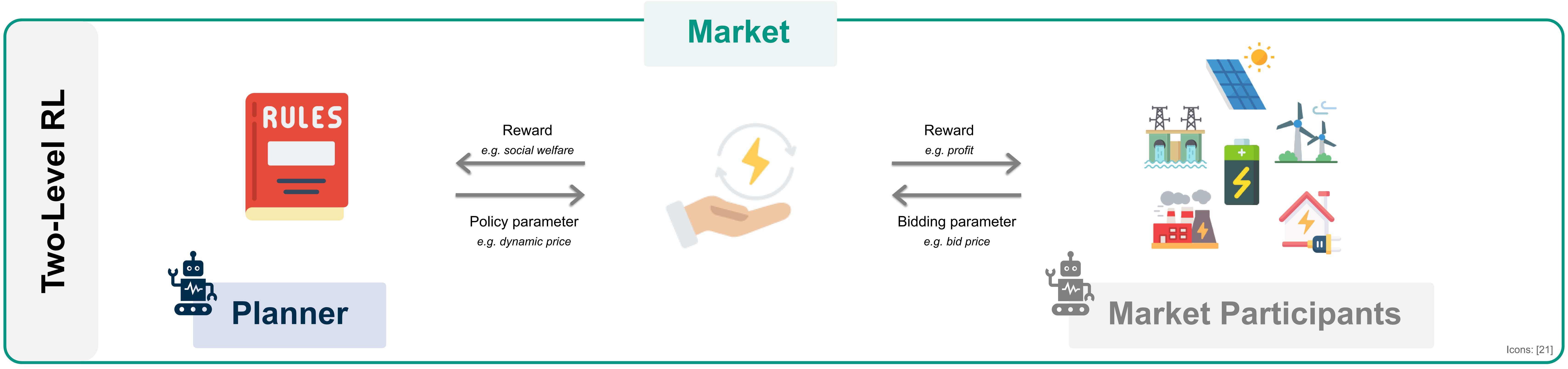
Two-Level Reinforcement Learning for Energy Market and Policy Design

From fixed rules to adaptive market mechanisms in agent-based electricity markets



Electricity Market Design

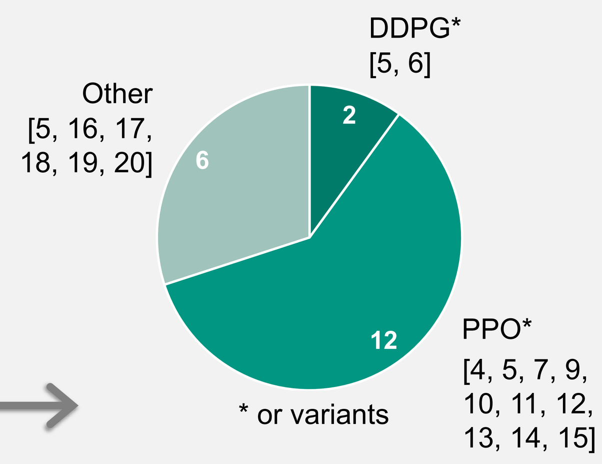
- The **energy transition** requires not only technological transformation of the energy system but also substantial **adaptation of regulatory and market frameworks.**
- In Germany, **major reforms** are **forthcoming** (e.g., EEG 2027, AgNes 2029, capacity market 2032).
- Existing **European electricity market design research** is dominated by optimization-based approaches, with comparatively **limited** use of equilibrium and **agent-based models** (approx. 72.5% vs. 15% and 12.5%, respectively) [1].
- The **design of effective market mechanisms** must account for **adaptive and strategic behavior** of agents, as emphasized by the Lucas critique [2].

Agent-Based Modeling with DRL

- **Strategic decision-making** of market participants can be effectively represented using **Deep Reinforcement Learning (DRL)** [3].
- Recent work extends multi-agent reinforcement learning **toward two-level formulations**, incorporating both agent behavior and **policy design**.
- Early **contributions** in this direction primarily focus on economic policy design, particularly **taxation** [4, 5].
- **Applications** to **energy system and electricity market** design remain **scarce**.
  - Optimization of social welfare via adaptive price caps in Cournot-type markets [6].
  - Joint minimization of system costs and maximization of self-consumption in energy communities through dynamic pricing policies [7].

Enabling Adaptive Planner Agents

- **Key challenges**
  - **Additional non-stationarity** induced by simultaneously learning agents and policy mechanisms.
  - **Scalability** to large populations of heterogeneous agents.
  - **Limited transparency and interpretability** of learned policies.
- **Algorithmic considerations** →
  - Predominant use of **Proximal Policy Optimization (PPO)**, due to:
    - Robustness under non-stationary conditions.
    - Favorable scalability in multi-agent settings.
- **Supporting techniques** →

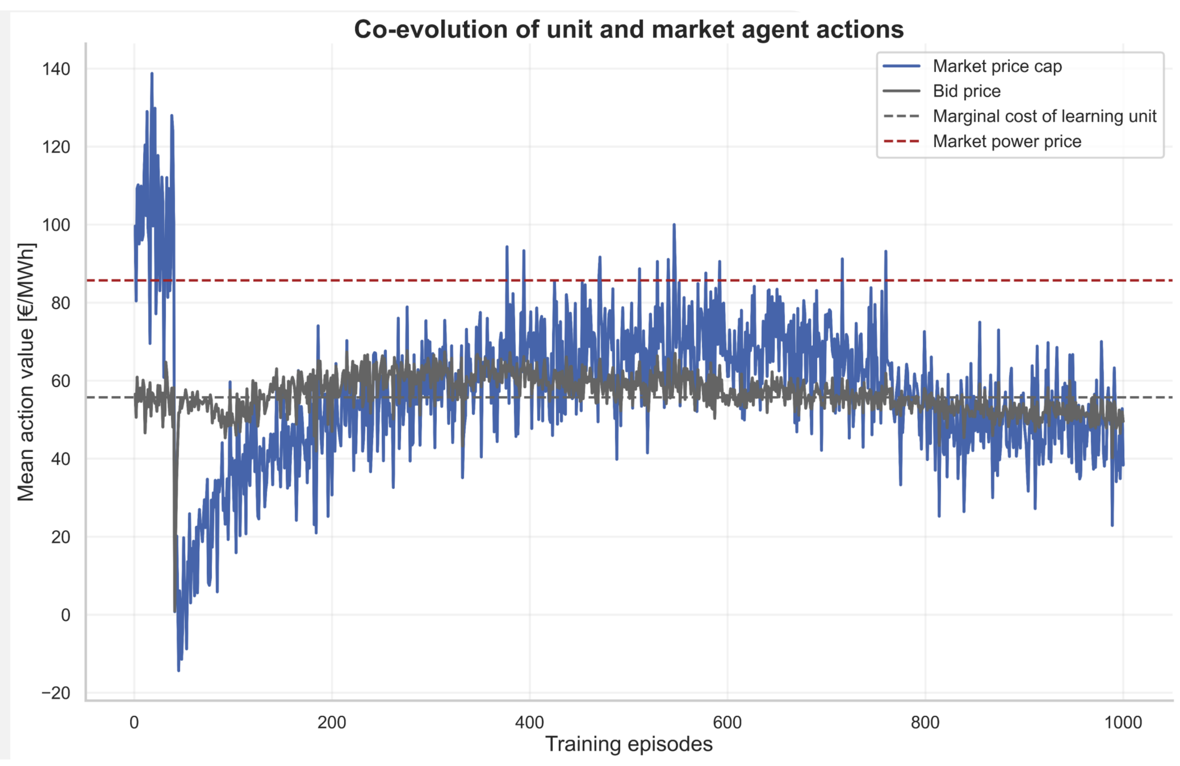


1. **Parameter Sharing** **[4, 5, 7, 10, 12, 20]**
2. **Entropy Regularization** **[4, 7, 10, 12, 13]**
3. **Curriculum Learning** **[4, 7, 12, 13]**

Future work

Analysis of **stability**, **convergence**, and **emergent system dynamics**
Applications: dynamic grid fees, capacity market design, …

Proof of Concept



- Structural extension of ASSUME-Framework
  - Exploratory results
  - Stylized example with market power [8]
  - Learn continuous price cap, inspired by [6]

Interpretation

- Market agent first increases price cap until all demand is satisfied
- Power plant unit learns to bid above marginal costs
- Market agent reduces price cap closer to merit order price

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References