

DigiPlat

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This project has received funding in the framework of the joint programming initiative ERA-Net Smart Energy Systems' focus initiative Digital Transformation for the Energy Transition, with support from the European Union's Horizon 2020 research and innovation program under grant agreement No 883973.

Exploring Multi-Market Strategy to Assess New Market Designs – using Reinforcement Learning

ABM4Energy 2025

Viktor Zobernig, Sarah Fanta, Stefan Strömer, Regina Hemm, Jochen L. Cremer, Laurens J. de Vries

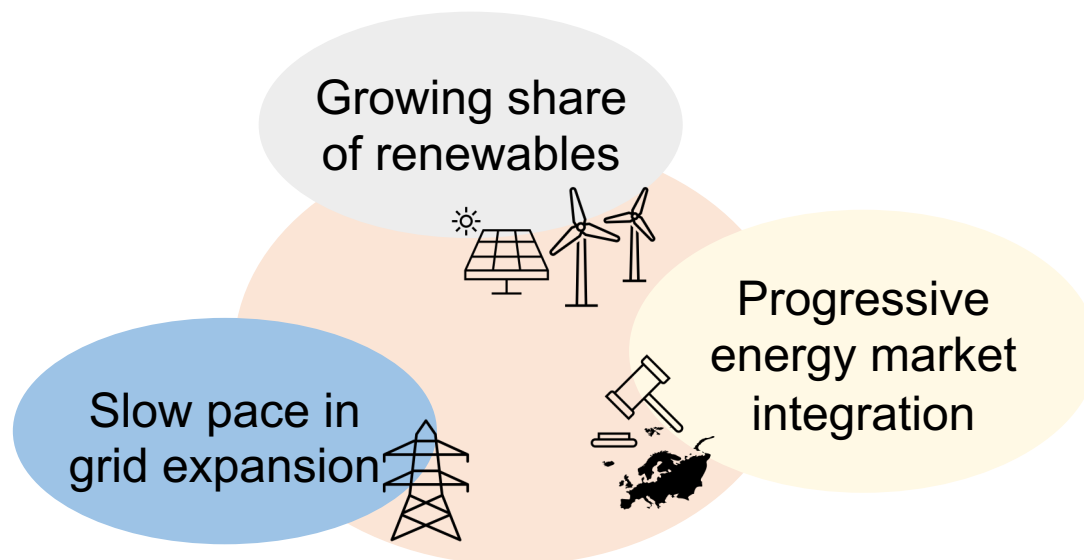
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Content



1. Energy Transition & Market Inefficiencies
2. Challenges in assessing Multi-Market Dynamics
3. Reinforcement Learning for Multi-Market Strategy Assessment
4. Results: Strategic Bidding in Four-Market Framework
5. Key Takeaways

Energy Transition & Market Inefficiencies



→ Increasing need and costs for redispatch in Europe

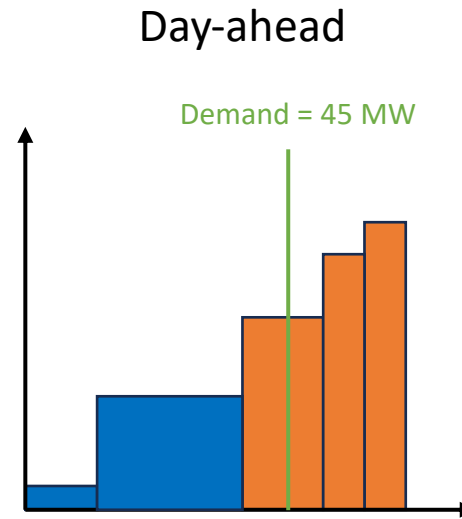
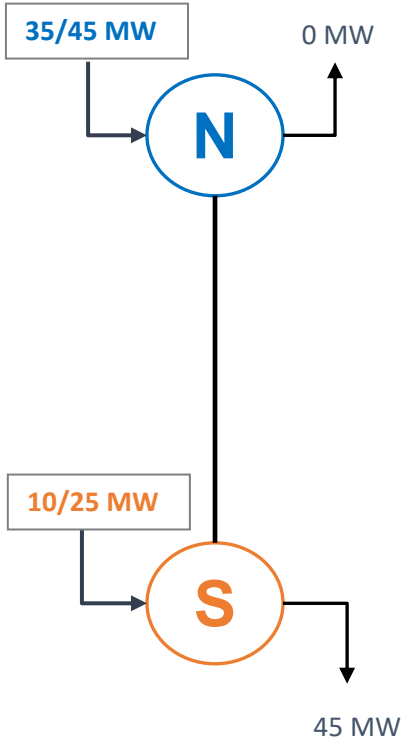
→ Challenges in assessing evolving market conditions for regulatory decision-making



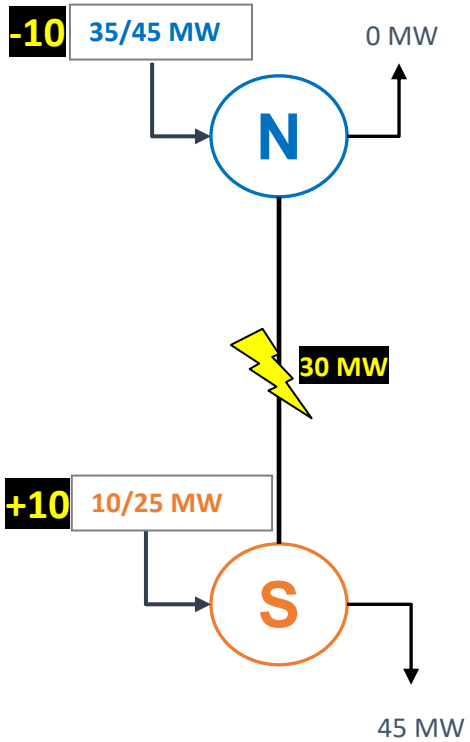
- Coordinating **electricity procurement across interconnected markets is a challenge** for suppliers, markets, and grid operators.
- Flexibility service providers (FSP) seek optimal bidding strategies for profitability.
- **Evaluating FSP bidding strategies is essential for understanding market outcomes** under a given design and guiding evidence-based improvements.

Challenges in Multi-Market Dynamics

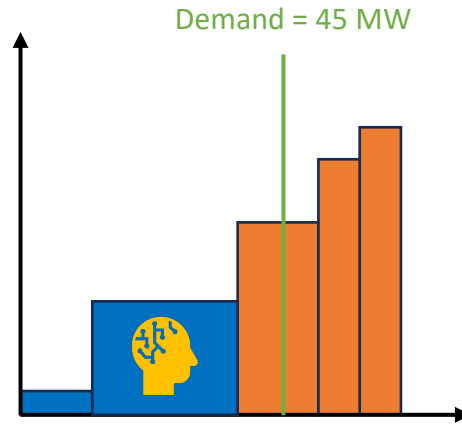
Multi-Market Bidding Complexity



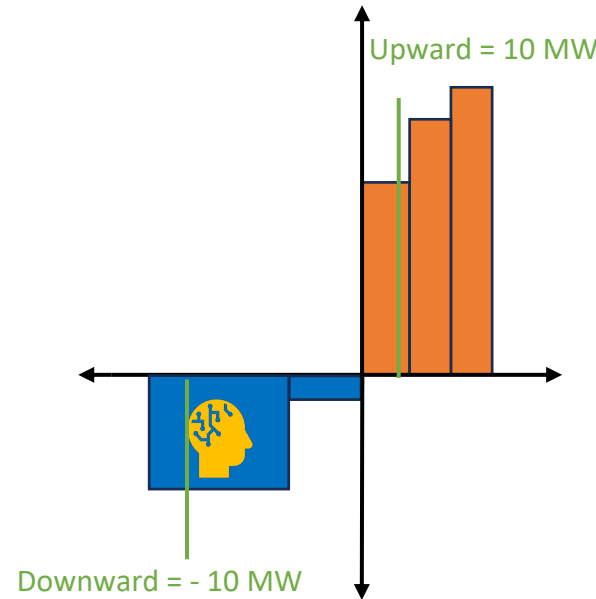
Multi-Market Bidding Opportunities



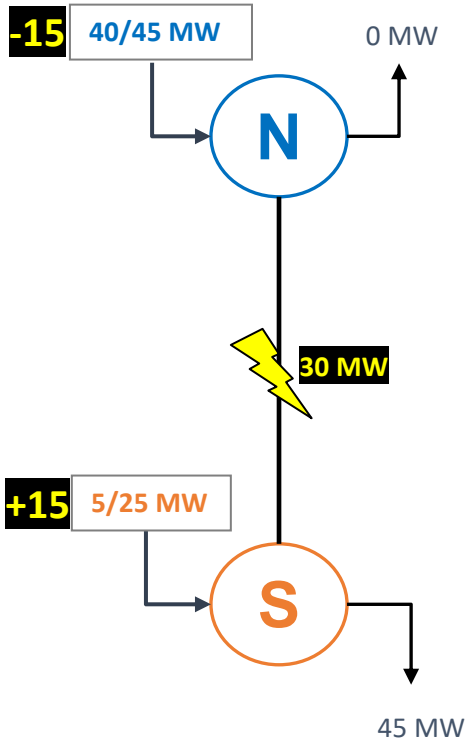
Day-ahead



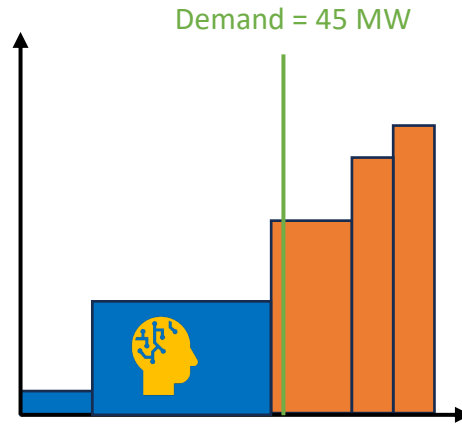
Redispatch



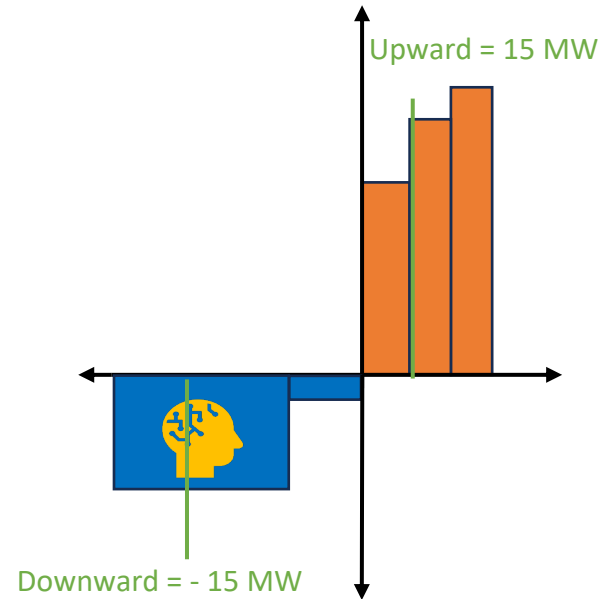
Multi-Market Bidding Opportunities



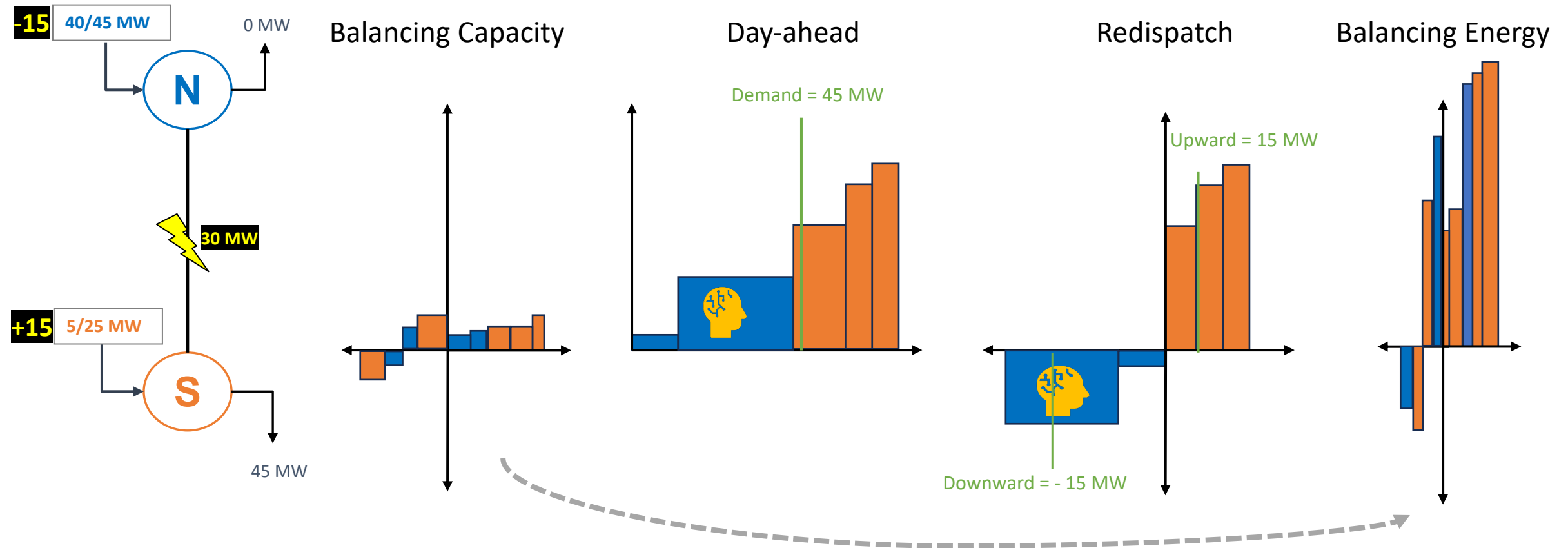
Day-ahead



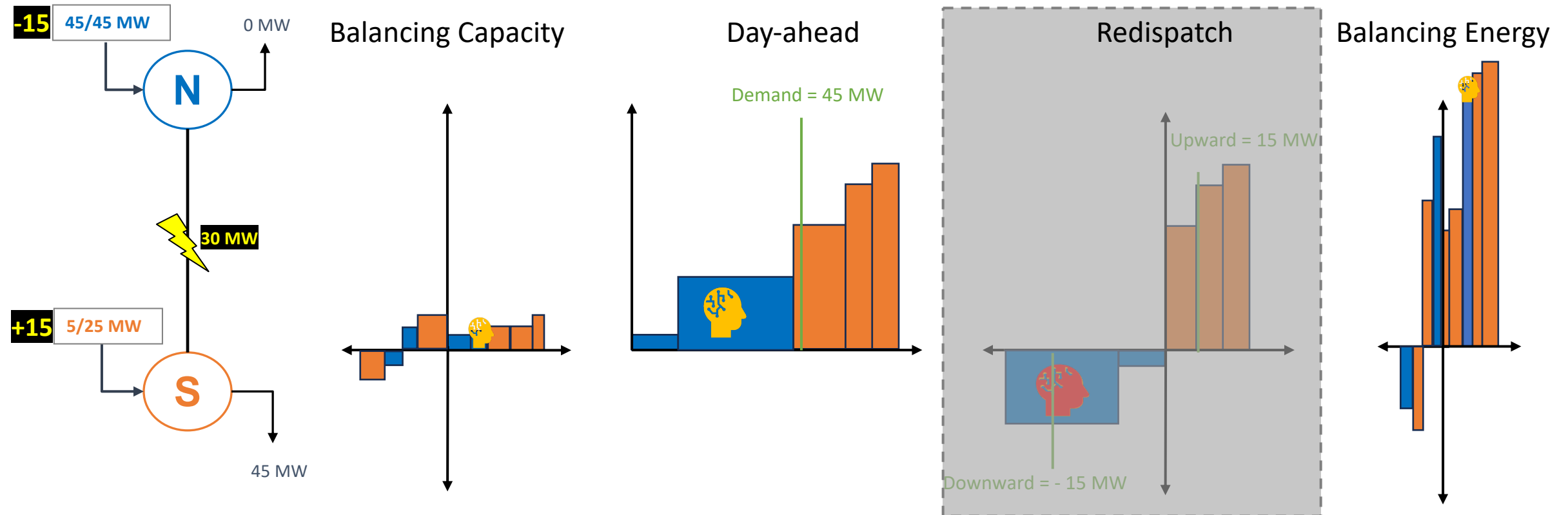
Redispatch



Multi-Market Bidding Opportunities

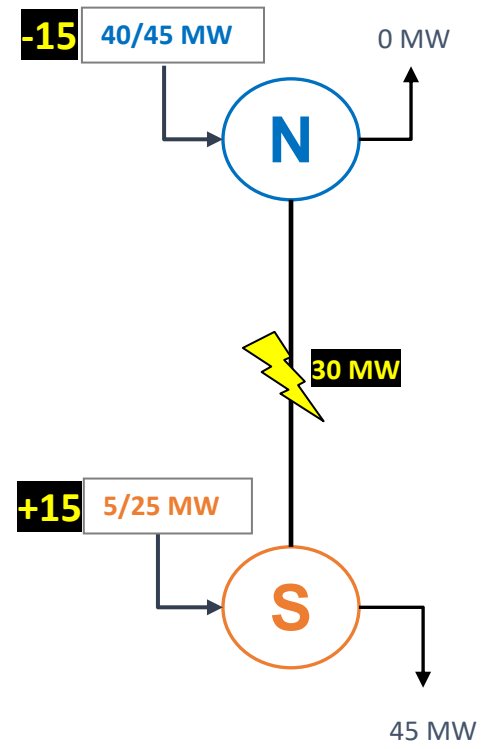


Multi-Market Bidding Uncertainty

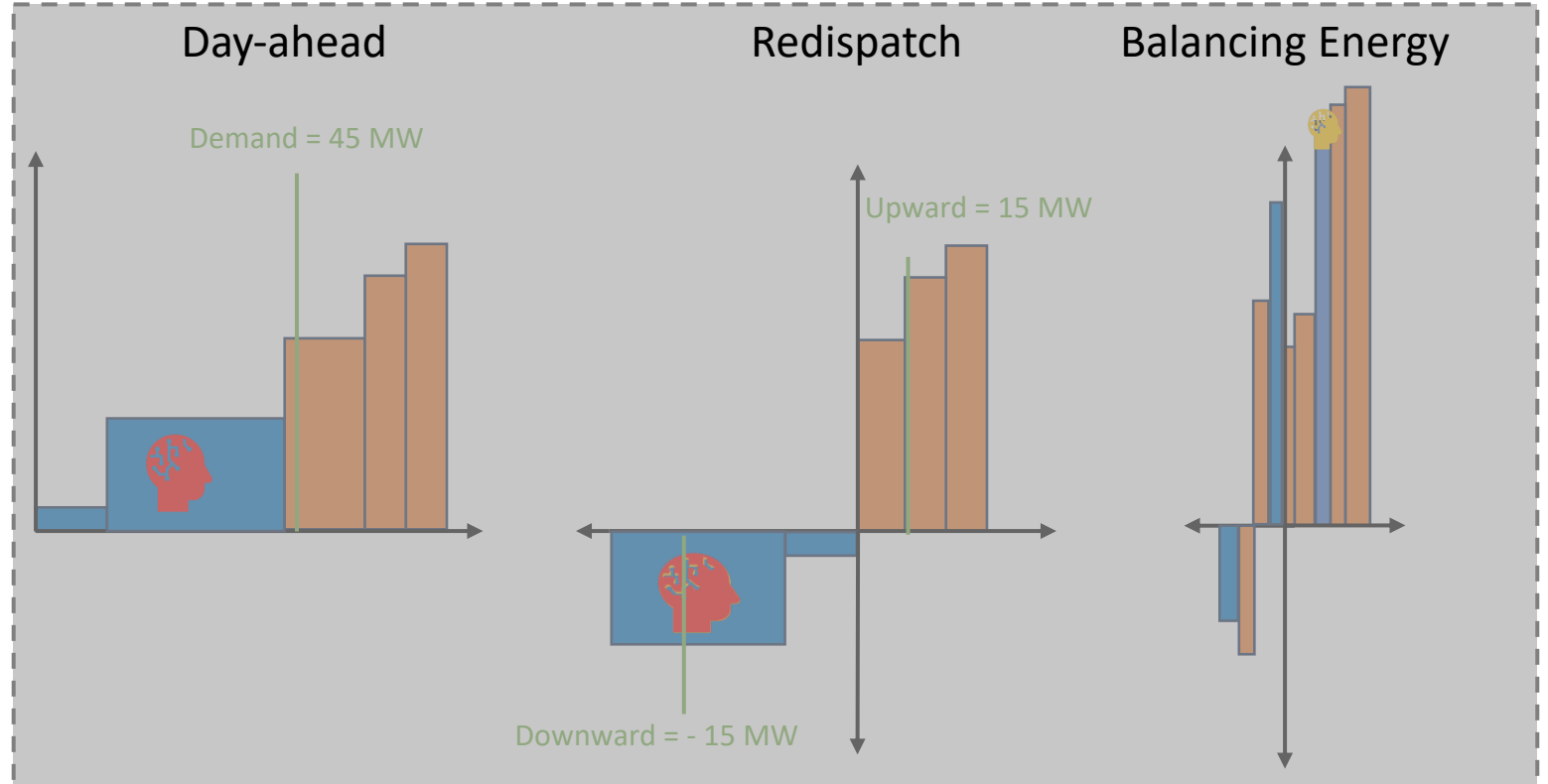
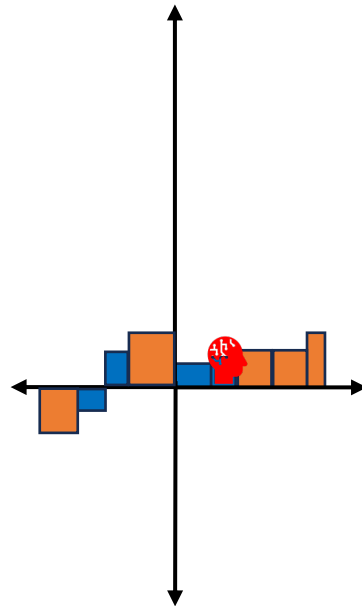


Uncertainty

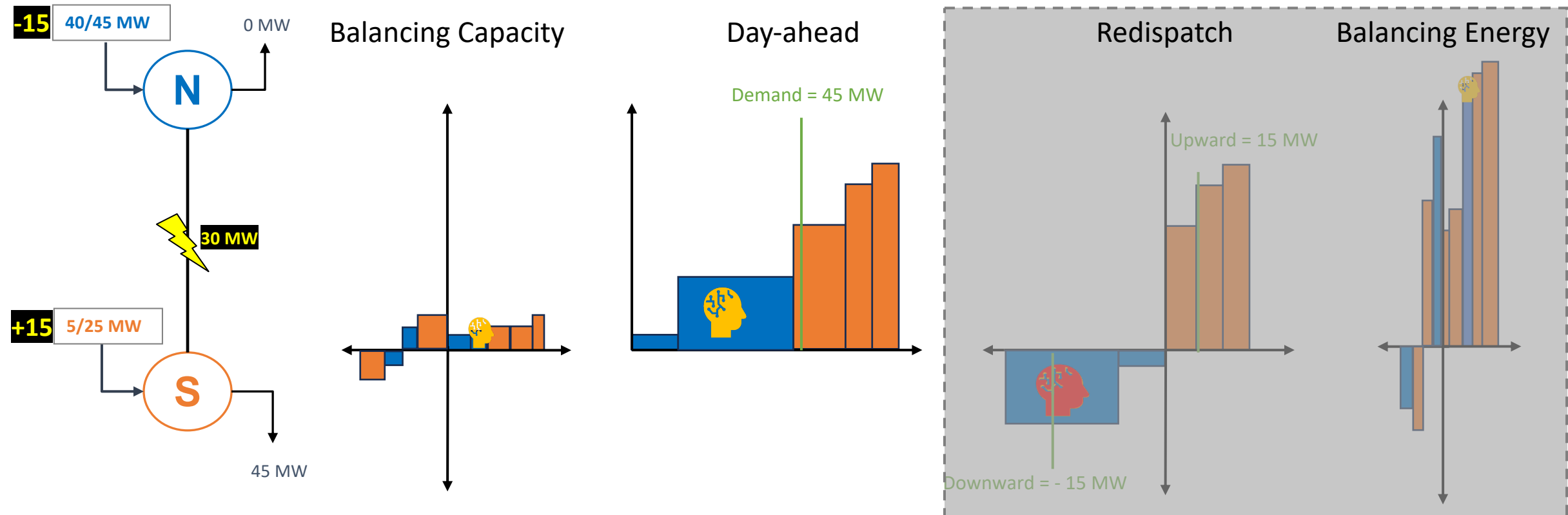
Multi-Market Bidding Uncertainty



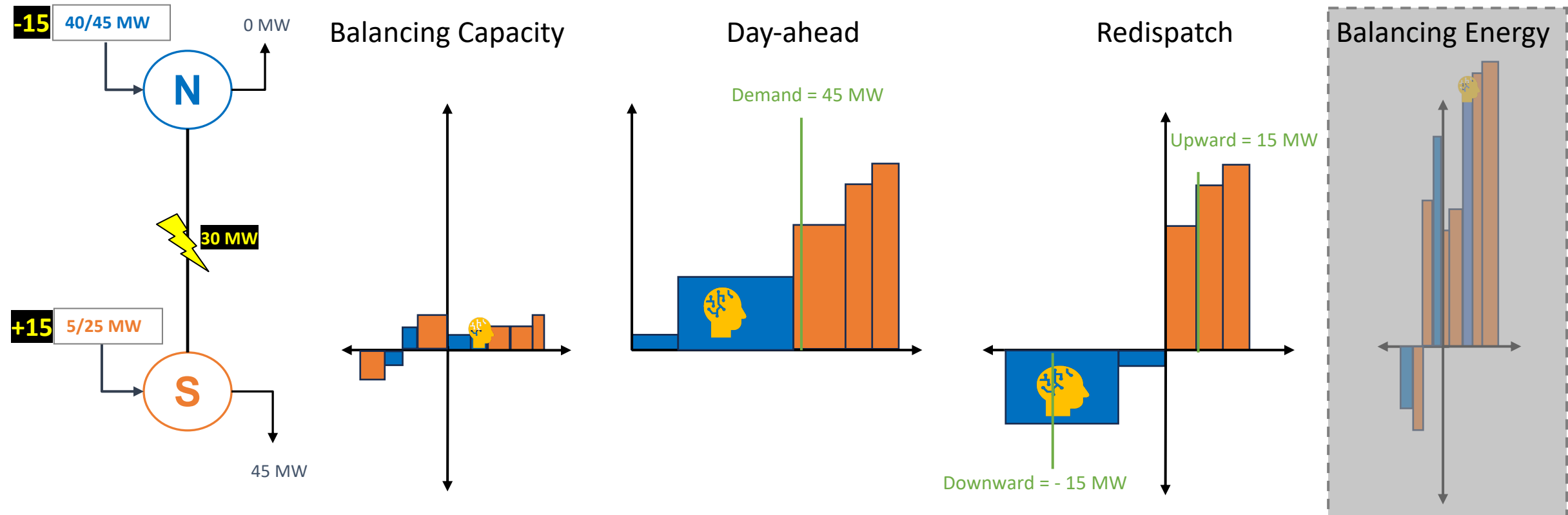
Balancing Capacity



Multi-Market Bidding Uncertainty



Multi-Market Bidding Uncertainty



Multi-Market Bidding Challenges



- Strategic bidding **opportunities** arise when the same energy is bid for the same hours across sequential markets, increasing the risk of gaming behavior.
- Market complexity increases due to **uncertainties** such as congestion emergence, weather deviations, and load forecast errors.

→ Limitations for Conventional Models

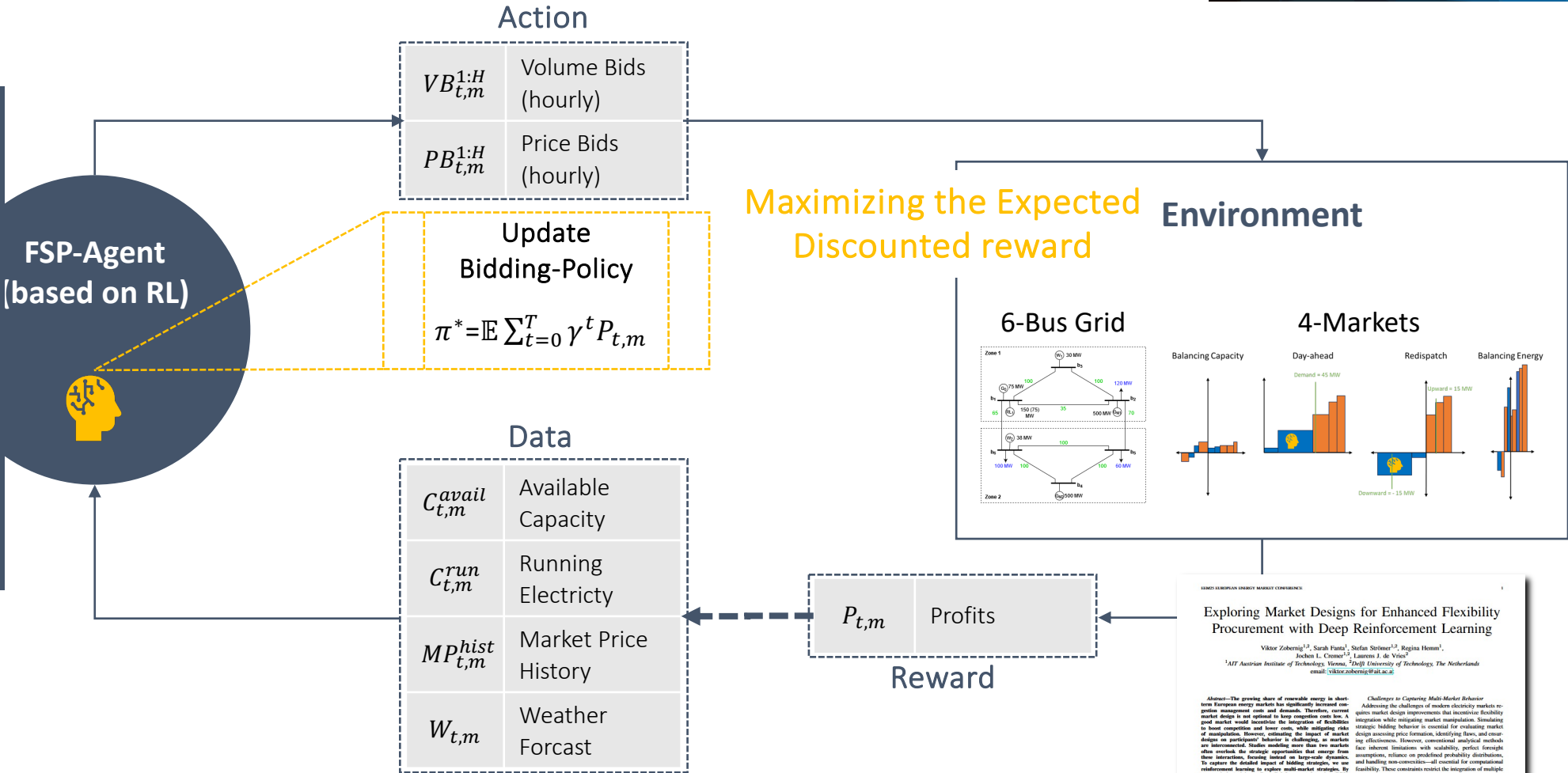
- **Scalability Challenges:** Conventional models (e.g., MPEC/EPEC) face difficulties scaling, especially when evaluating equilibrium strategies or managing simultaneous price and volume bids.
- **Assumption of Perfect Foresight:** Bi-level optimization methods rely on iterative adjustments of agents' decisions under the assumption of perfect foresight, which may overestimate the risk of strategic behavior.

→ Reinforcement learning (RL) is a promising alternative, demonstrating flexibility and adaptability in overcoming these limitations in similarly complex tasks

Reinforcement Learning (RL)

FSP- Agent based on RL

- Using Actor-Critic Neural Network Architecture
- Actor networks, takes data as input and outputs an action
- Critic evaluates the action taken for the given data based on received reward – gives the Feedback for the Actor



Exploring Market Designs for Enhanced Flexibility Procurement with Deep Reinforcement Learning

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 Jochen Li, Christof¹, Laurens J. de Vries³

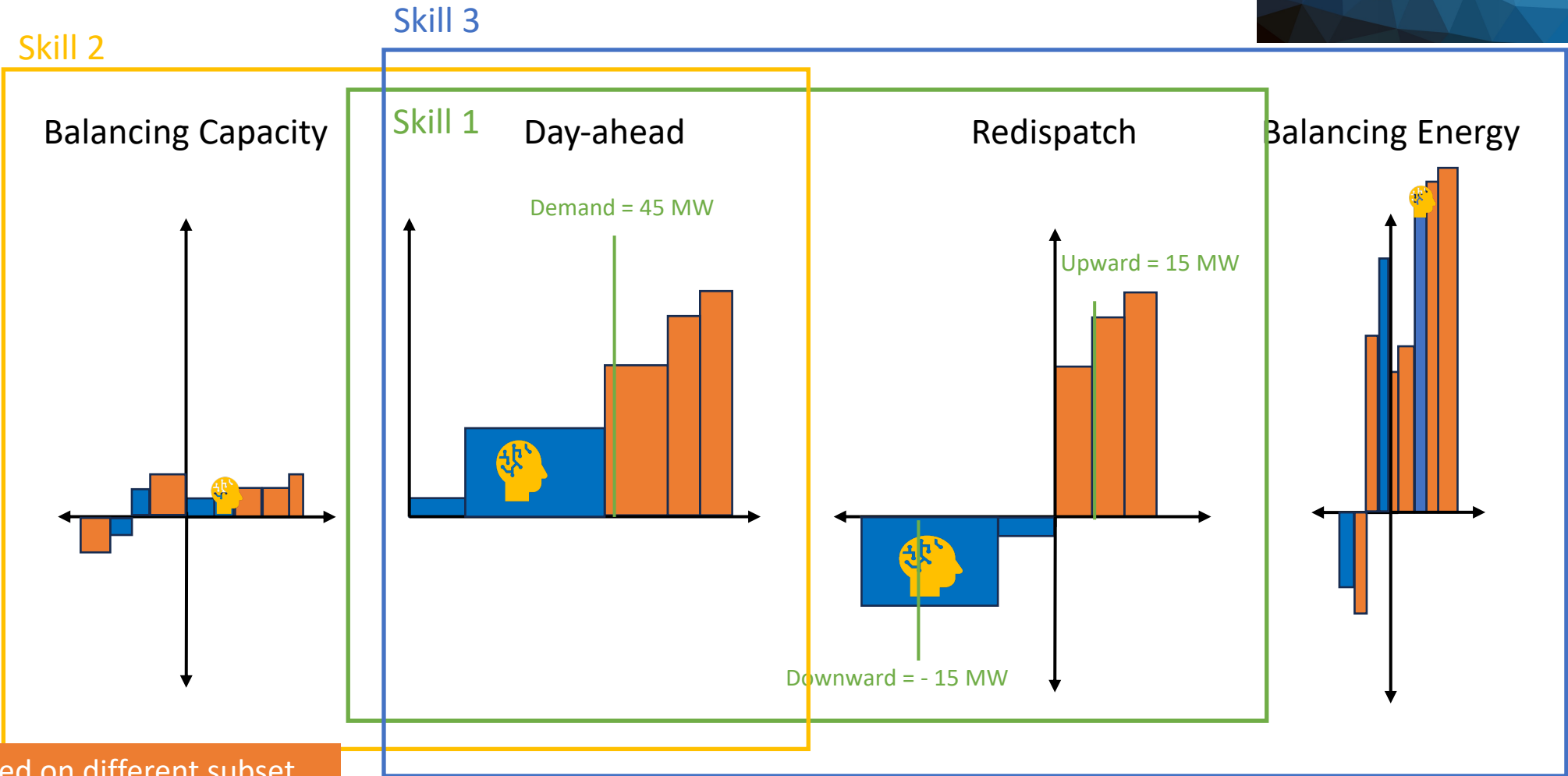
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Abstract—The growing share of renewable energy in short-term European energy markets has significantly increased over-purposes management costs and demands. Therefore, current market design is not optimal to keep competition costs low. A good market would incentivize the integration of flexibility to boost competition and lower costs, while mitigating risks of manipulation. Hence, optimizing the layout of market design on participants' behavior is challenging, as markets are interconnected. Studies modeling more than two markets often overlook the strategic opportunities that emerge from these interactions, focusing instead on large-scale dynamics. To capture the detailed impact of bidding strategies, we use reinforcement learning to explore multi-market strategies. By progressively training a Deep Reinforcement Learning (DRL) agent as a market participant from replicating established market mechanisms to exploring novel market mechanisms, we achieve a significant performance gain. Our results show that a structured approach that iteratively explores bidding strategies outperforms conventional approaches. We validate our approach against established four-market studies, then evaluate it in two progressively complex four-market case studies spanning a 4-horizon network, including bilateral trading and fuel costs. Results show that our DRL-based method significantly improves performance but also highlights challenges when market opportunities expand drastically.

Index Terms—Agent Based Model, Deep Reinforcement Learning, Electricity Markets, Market Power, Strategic Bidding

Challenges in Capturing Multi-Market Behavior
 Addressing the challenges of modern electricity markets requires market design improvements that incentivize flexibility integration while mitigating market manipulation. Simulating strategic bidding behavior is essential for evaluating market design scenarios, price formation, identifying flows, and ensuring effectiveness. However, conventional analytical methods face inherent limitations with scalability, perfect foresight assumptions, reliance on predefined probability distributions, and handling non-convexities—all essential for computational feasibility. These constraints restrict the integration of multiple markets, agents, or time steps, significantly affecting the representation of strategic opportunities and risks. To model strategic behavior, conventional approaches determine Nash equilibria by formulating payoff functions, as in game theory, or by modeling each market participant as an optimization problem constrained by others' equilibrium conditions—formulated as EPIC (Equilibrium Problem with Equilibrium Constraints) and MPEC (Mathematical Program with Equilibrium Constraints). Notable examples include [1], which demonstrates systemic risks and dynamics of inelastic gaming, offering insights in the demand strategy even under perfect competition in market-based markets [2].

Domain-Informed Curriculum Learning **DigIPlat**

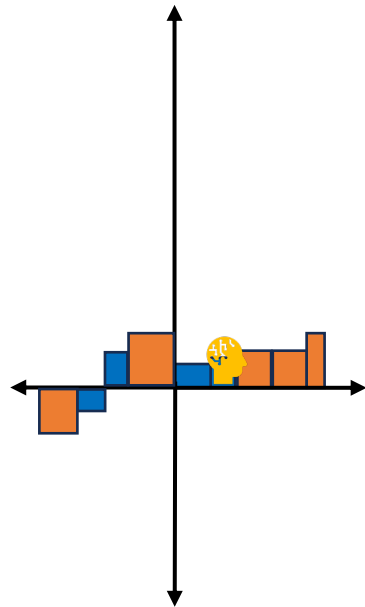


Training skill, based on different subset of the underlying interconnected states!

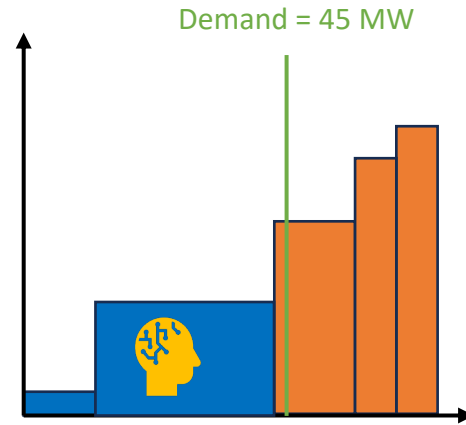
Domain-Informed Curriculum Learning



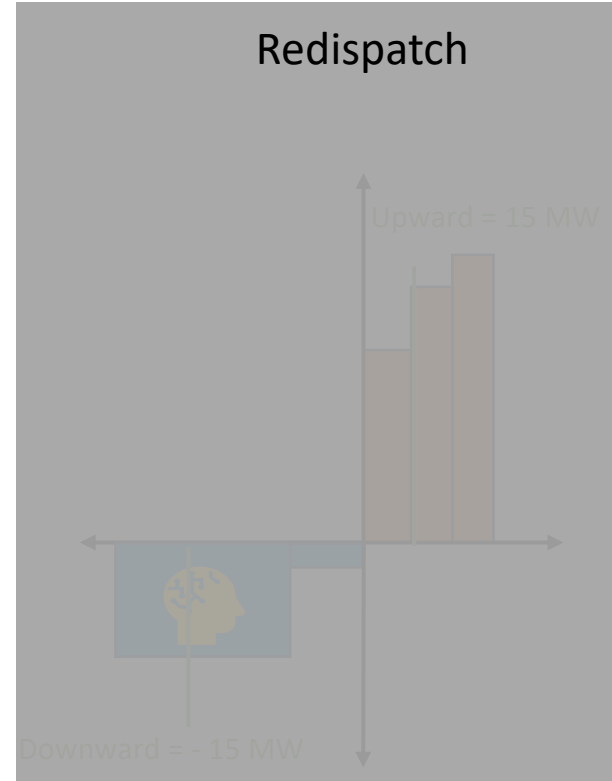
Balancing Capacity



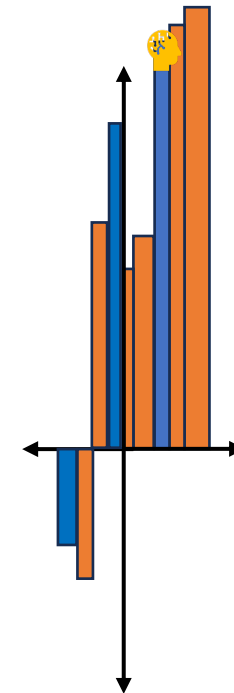
Day-ahead



Redispatch



Balancing Energy



-Stage

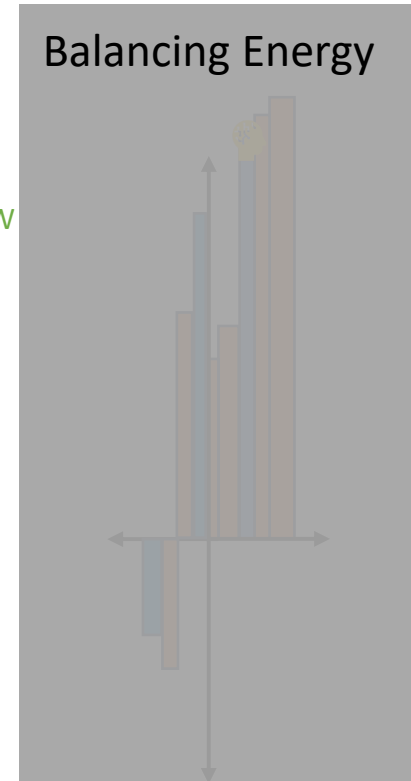
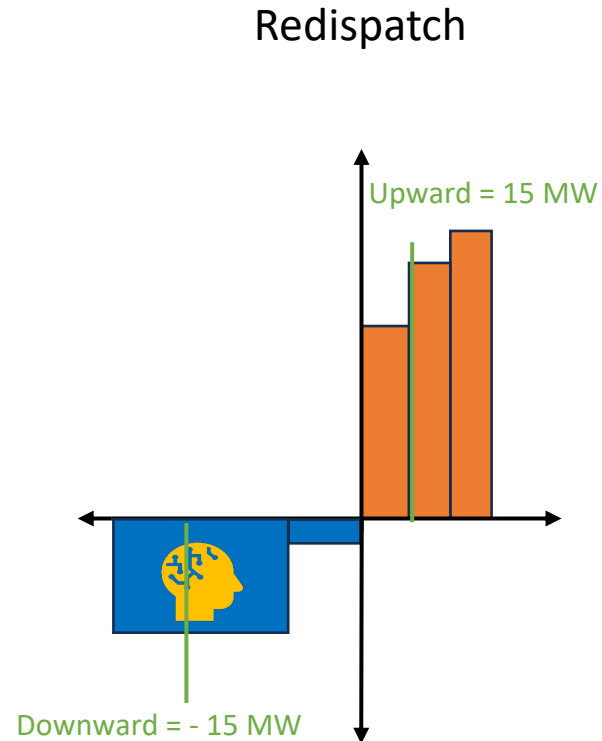
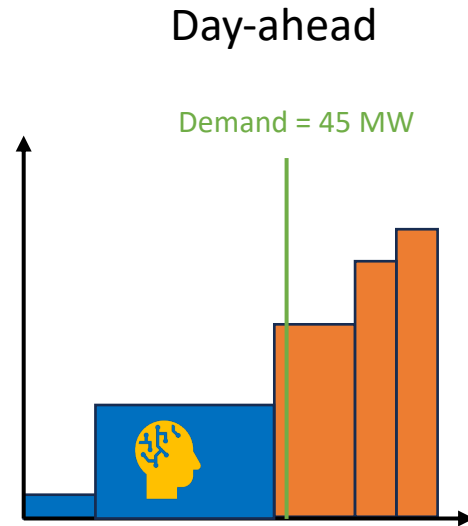
1-

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Domain-Informed Curriculum Learning **DigIPlat**



-Stage

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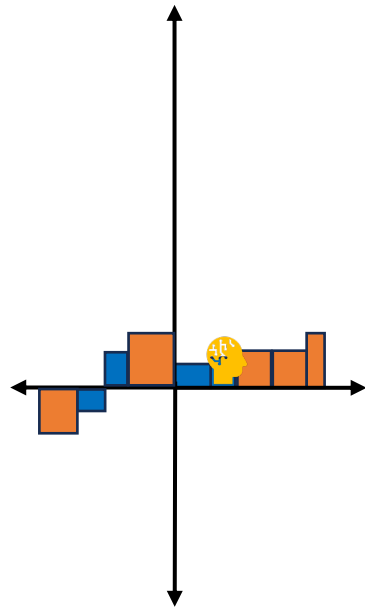


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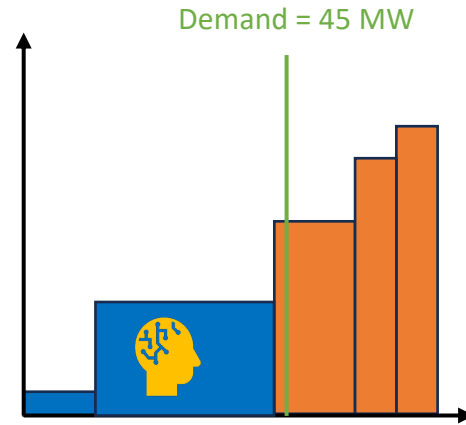
Domain-Informed Curriculum Learning



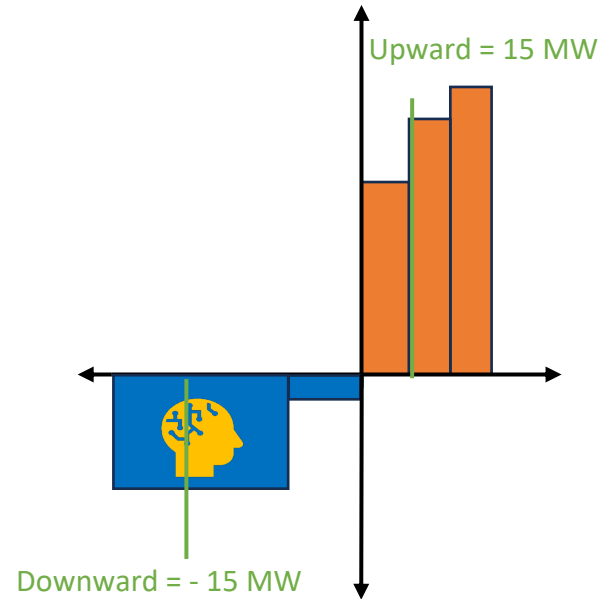
Balancing Capacity



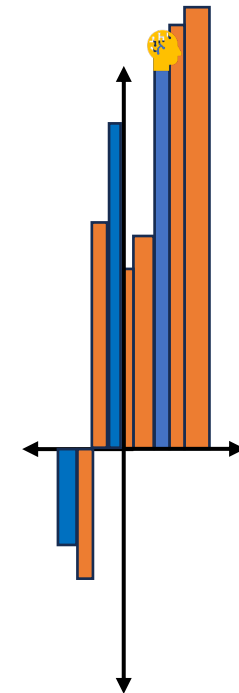
Day-ahead



Redispatch



Balancing Energy



-Stage

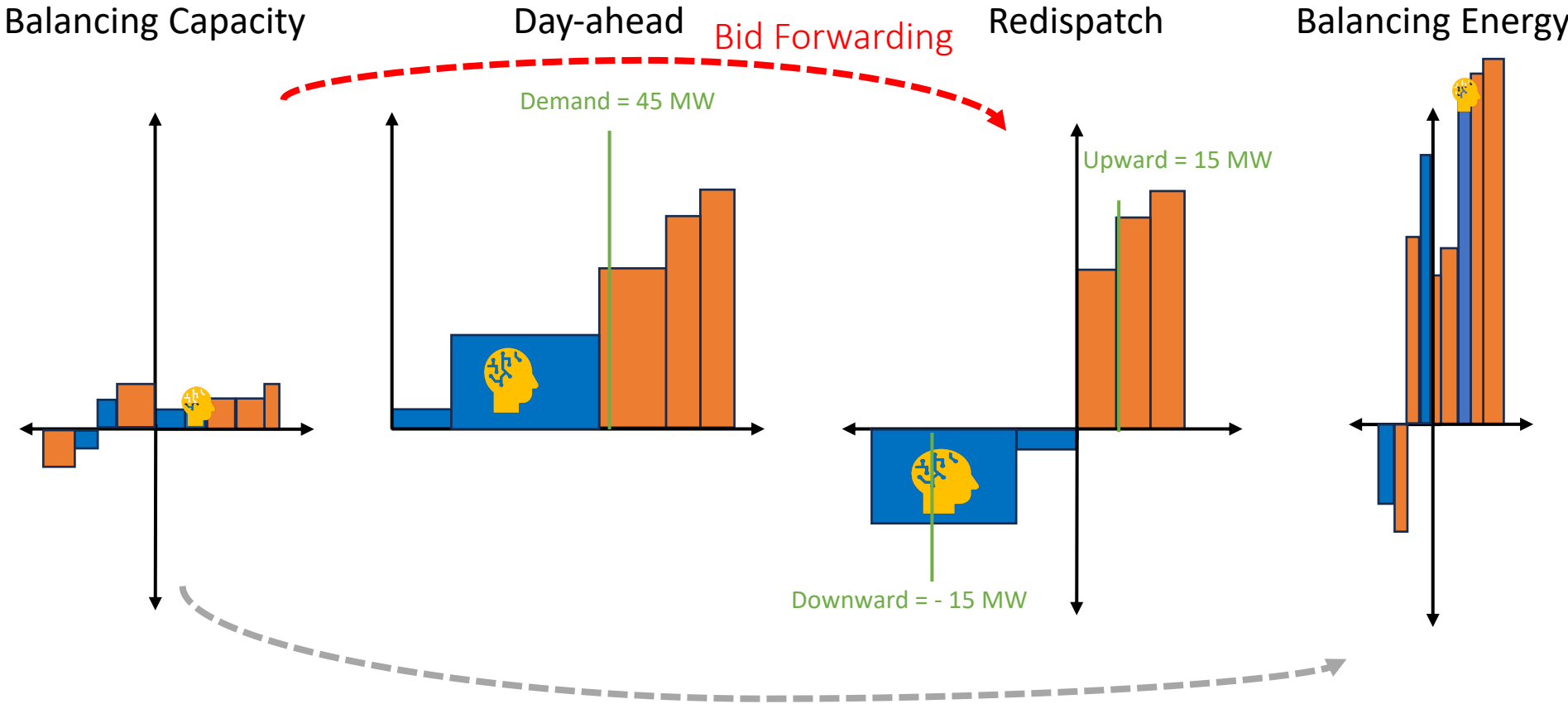
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Testing Stage Interactions

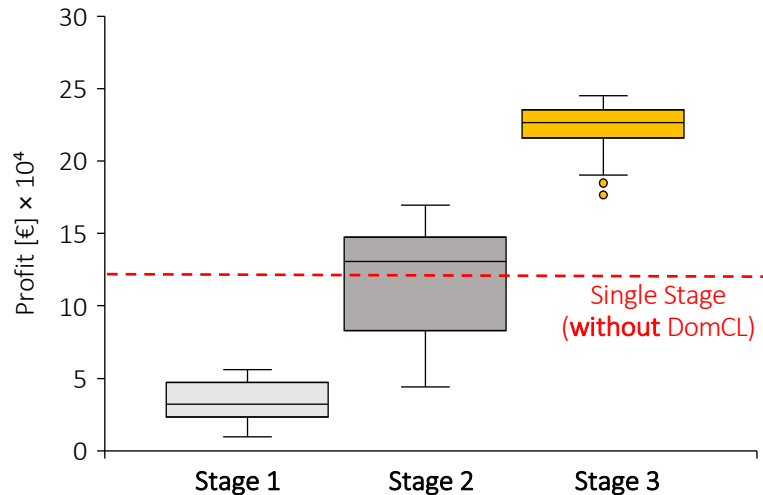


Results

Results



Standard RL vs. Domain-Informed RL



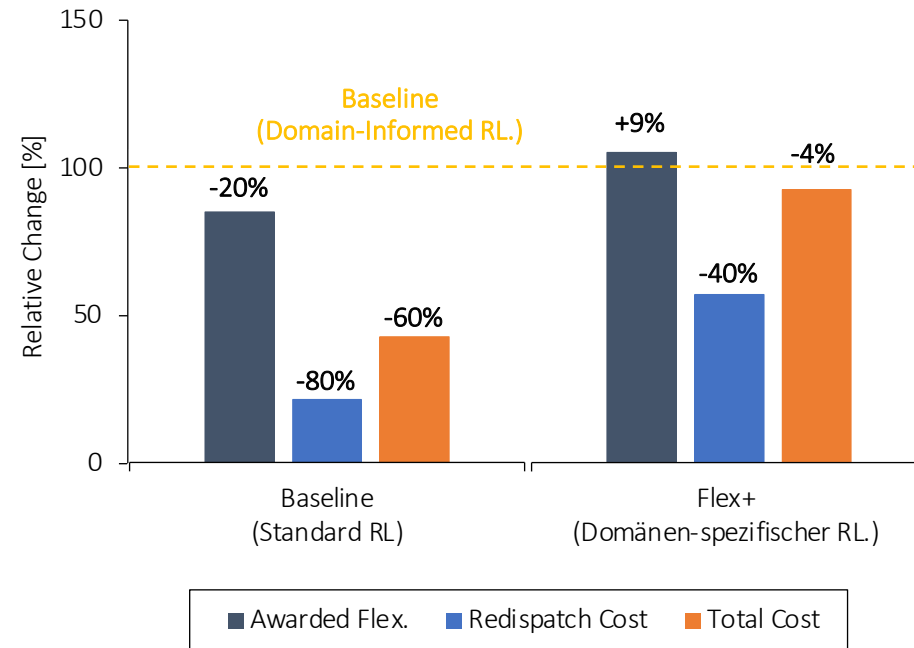
- The domain-informed curriculum learning (DomCL) approach builds on skills acquired in earlier stages.
- It uncovers additional synergies by exploiting a combined strategy in the final stage.
- In the absence of DomCL, learning tends to average across varying interdependencies due to weaker feedback signals from past decisions.

Results



- The domain-informed RL agent enables a more efficient training process and significantly improves the strategy for profit-maximizing behavior.
- However, the newly introduced market uncertainties in the Flex+ scenario lead to a slight decline in achieved profits, as they promote more conservative behavior.

Changes in Strategy Considering Domain-Informed RL



Key Takeaways



- Ongoing changes in electricity markets lead to rising congestion management costs. **Whether new market designs can resolve these issues or worsen them through strategic behavior (gaming) remains difficult to assess.**
 - Conventional models often fail to capture such dynamics accurately. **Reinforcement Learning (RL) enables scalable modeling while explicitly considering uncertainty.**
- Our domain-specific RL agent provides a **training-efficient approach to realistically model profit-driven behavior in multi-market systems.**
- Results show that the agent learns to exploit local market power but, **under increasing uncertainty (Flex+ scenario), converges toward more conservative, less exploitative behavior.**



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tba



Results

