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Electronic Information Technology Development Webinar
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“Digital twins” for industrial energy management: enhancing demand-side flexibility with linear optimisation* and reinforcement learning**

**Lerch, Philipp, Fabian Scheller, David G. Reichelt, and Thomas Bruckner. "Flexibility cost savings potential for chlor-alkali electrolysis plants: a model-based analysis of technical and procedural efficiencies." (to be submitted), 2022.*

***Biemann, Marco, Philipp Gunkel, Fabian Scheller, Lizhen Huang, and Xiufeng Liu. "Reinforcement learning with real-time pricing in HVAC control." (to be submitted), 2022.*

Motivation Statement

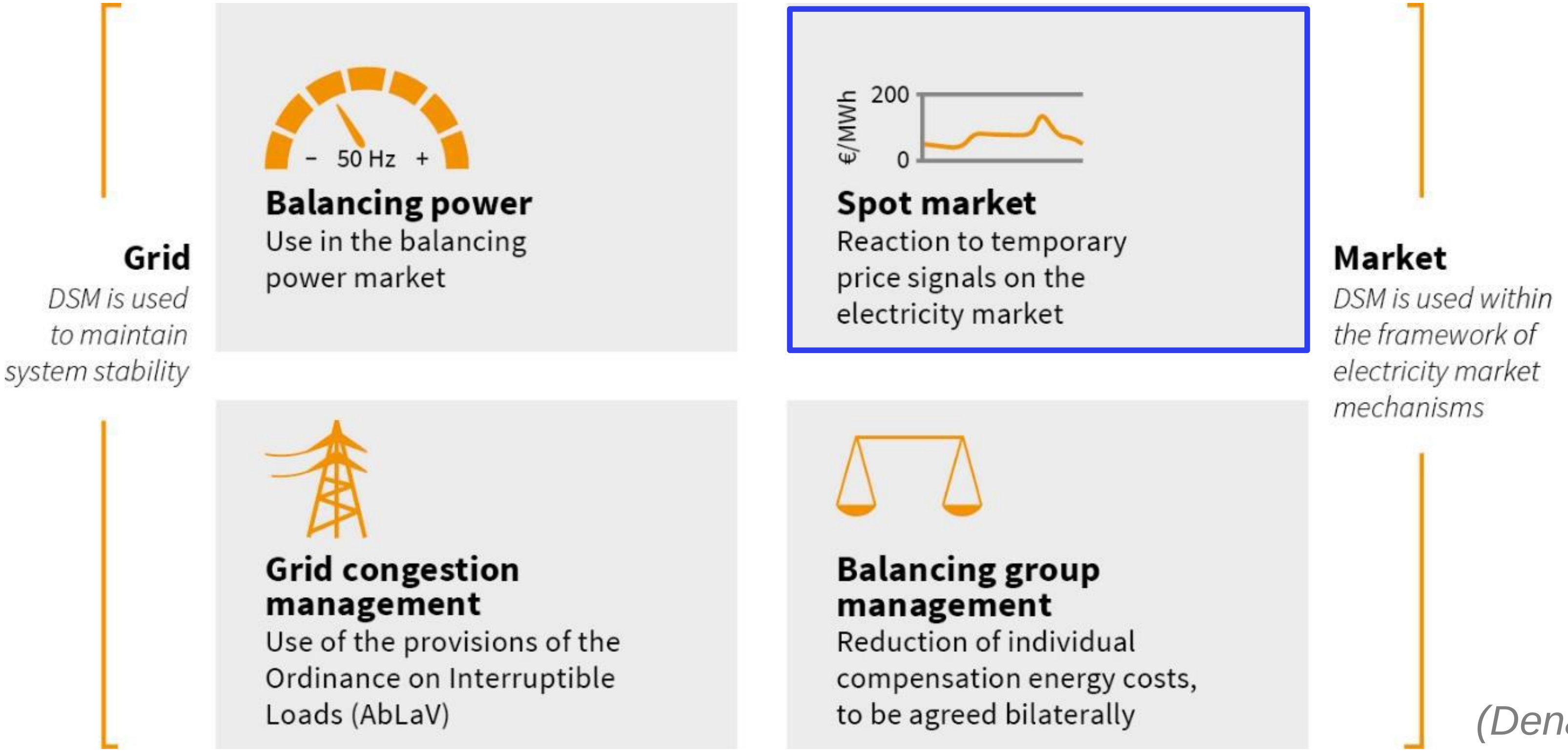
In times of rising energy costs, flexible loads in the industry can be a key factor for system stability but also for industrial competitiveness.

- **Load flexibility is required** to integrate renewable energy and to reduce consumption in peak-demand periods
- **Rescheduling of industrial loads contributes to** system stability of the electricity sector and also to **cost reduction of the producing industry**
- Advanced **digital infrastructure provides decision-suppport** in utilising demand side flexibility
- This presentation highlights…
  - → **flexibility advantages through data-driven simulations (digital models vs. digital twins)**
  - → **economic benefits of flexible industrial loads (model-based vs. model-free frmw.)**

Source: Dena (German Energy Agency). „Industrial Demand Side Flexibility in China - German Experiences – Status Quo and Potential in China – Policy and Market Recommendations." 2019.

Demand Side Management

Demand side management is the adjustment (reduction, increase, shift) of a part of the consumption in a specific period of time, e.g., due to the current spot market price.



(Dena,2019)

- Economic potential of potential flexibility of industrial loads need to be assessed. Due to the complexity of the industrial processes, digital twins or models are helpful.

Source: Dena (German Energy Agency). „Industrial Demand Side Flexibility in China - German Experiences – Status Quo and Potential in China – Policy and Market Recommendations." 2019.

Digital Twin

A Digital Twin is a virtual representation that serves as the real-time digital counterpart of a physical object or process.

- **Digital Twins are virtual copies of physical systems** which comprise quantitative decision-support tools

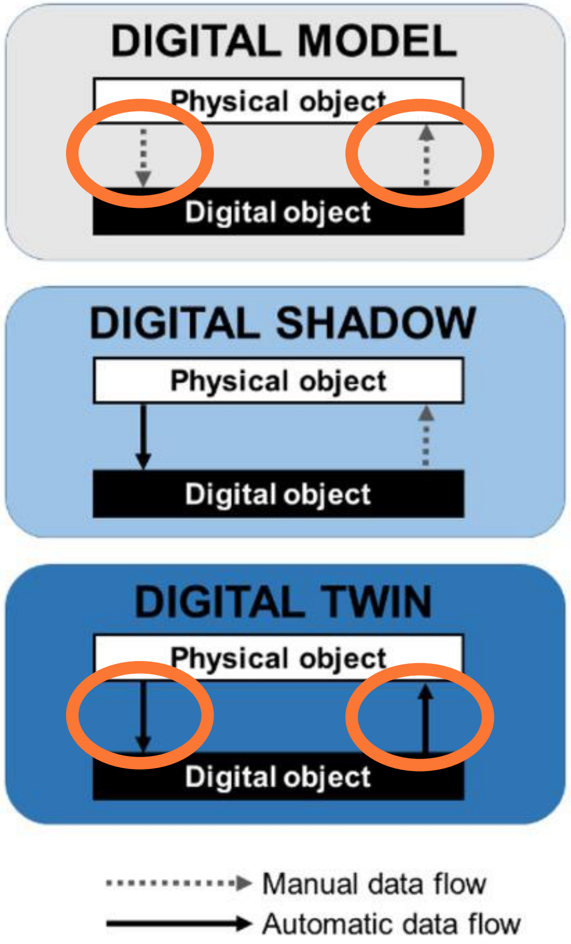
  → **Flexibility management of industrial loads**

  → **Data-driven decision-support or -making**

- Digital Twins, Digital Shadows, and Digital Models are differentiated by their data integration levels

- **Digital Twins have fully integrated data flows in both directions** in contrast to Digital Models or Shadows

(Nikula et al., 2020)

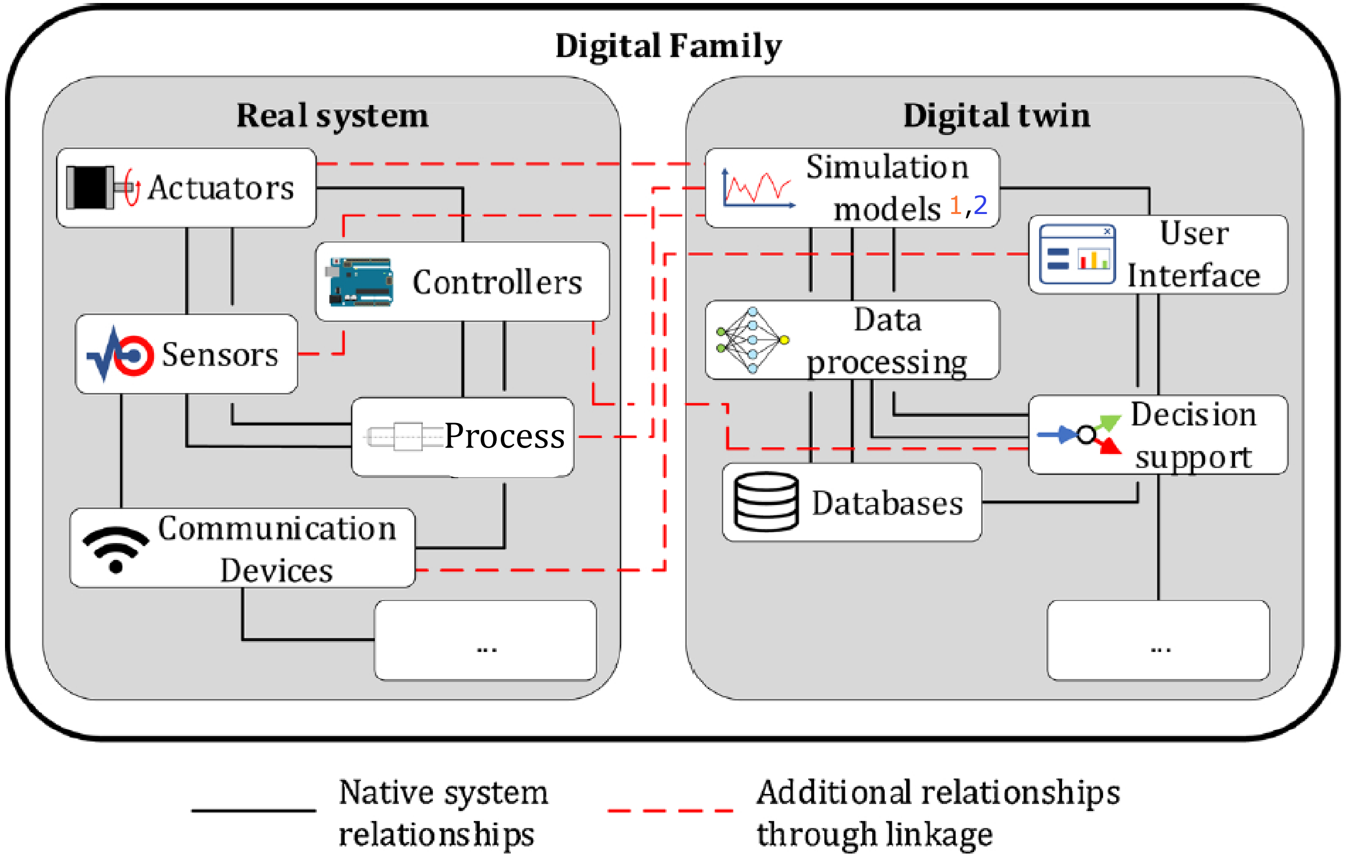


Source: Nikula, Riku-Pekka, Marko Paavola, Mika Ruusunen, and Joni Keski-Rahkonen. "Towards online adaptation of digital twins." Open Engineering 10, no. 1 (2020): 776-783. https://doi.org/10.1515/eng-2020-0088.

Digital Production

To fully harvest the power of a Digital Twin in optimising the production process in real-time, a fully data-driven and integrated production process is required.

(Glatt et al., 2021)



Practical challenges of digital twins:

Integrated data flows but also sensors and controllers are missing (Wagner et al, 2019)

→ IoT is the basis for digital decision-support

Examples of quantitative decision-support tools:

1) Mathematical optimisation

2) Reinforcement learning

→ Methods need to be aligned with the problem

Source: Glatt, Moritz, et al.. "Modeling and implementation of a digital twin of material flows based on physics simulation." Journal of Manufacturing Systems 58 (2021): 231-245. https://doi.org/10.1016/j.jmsy.2020.04.015. Wagner, Raphael, et al. "Challenges and potentials of digital twins and industry 4.0 in product design and production for high performance products." Procedia CIRP 84 (2019): 88-93. https://doi.org/10.1016/j.procir.2019.04.219.

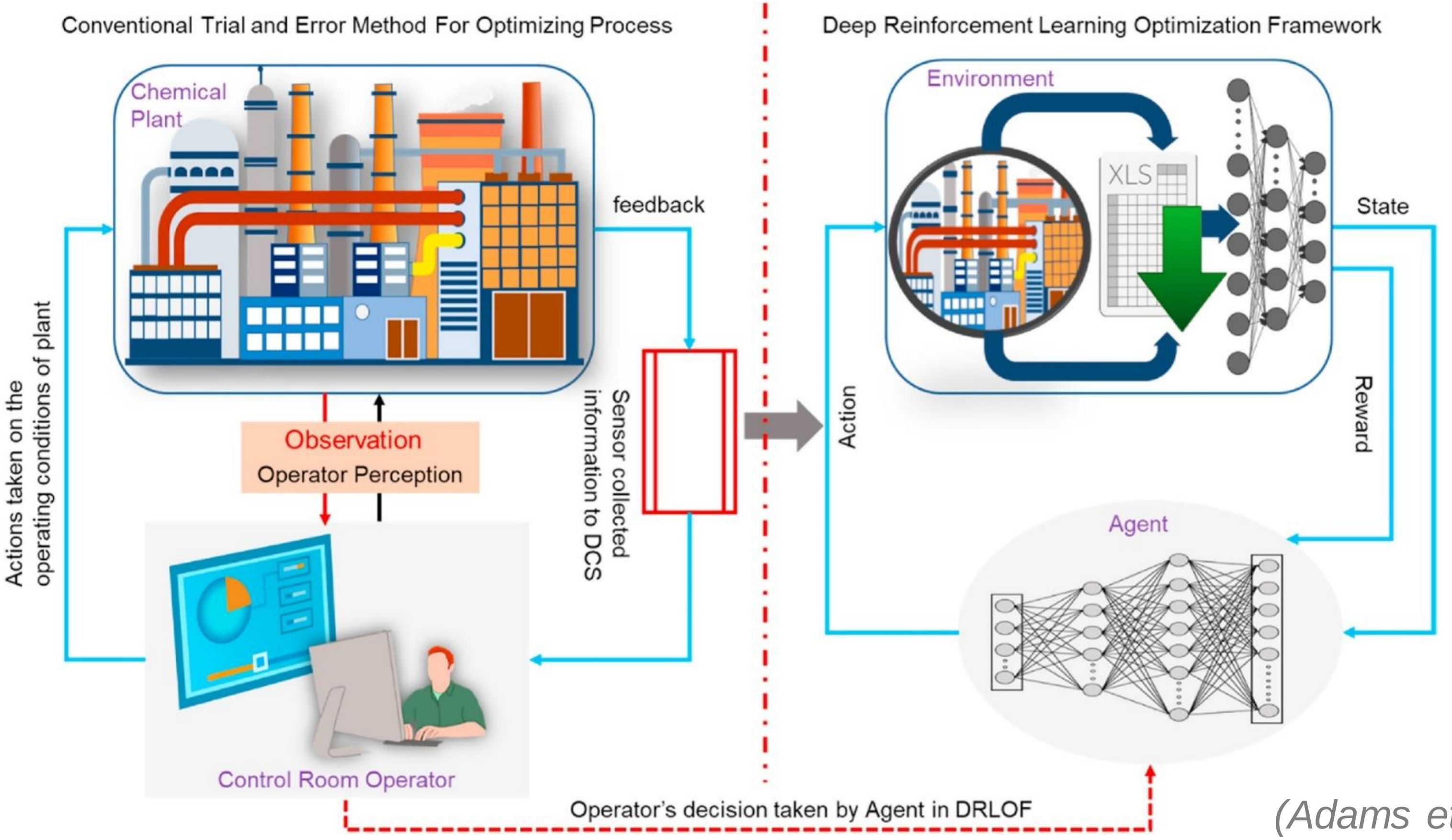
Decision Support

Quantitative decision-support tools for digital processes are moving from model predictive to cognitive adaptive frameworks.

Setpoint decisions are made by controlroom operators:

- *feedback from the plant*
- *previous data collected*
- *own experience*
- *retrospective modeling results*

→ ***operators with high domain knowledge*** *(actions affect the steadiness of the operation, profits, energy conservation)* *(Adams et al., 2021)*



Setpoint decisions are made by computer agents:

- *Agents are operator*
- *Process actions are optimised in line with the reward function*
- *Environment is given by process and is stochastic*

→ ***Agent gains experience*** *from the domain knowl-edge of the environment to make the right decisions*

(Adams et al., 2021)

Source: Adams, Derrick, Dong-Hoon Oh, Dong-Won Kim, Chang-Ha Lee, and Min Oh. "Deep reinforcement learning optimization framework for a power generation plant considering performance and environmental issues." Journal of Cleaner Production 291 (2021): 125915. https://doi.org/10.1016/j.jclepro.2021.125915.

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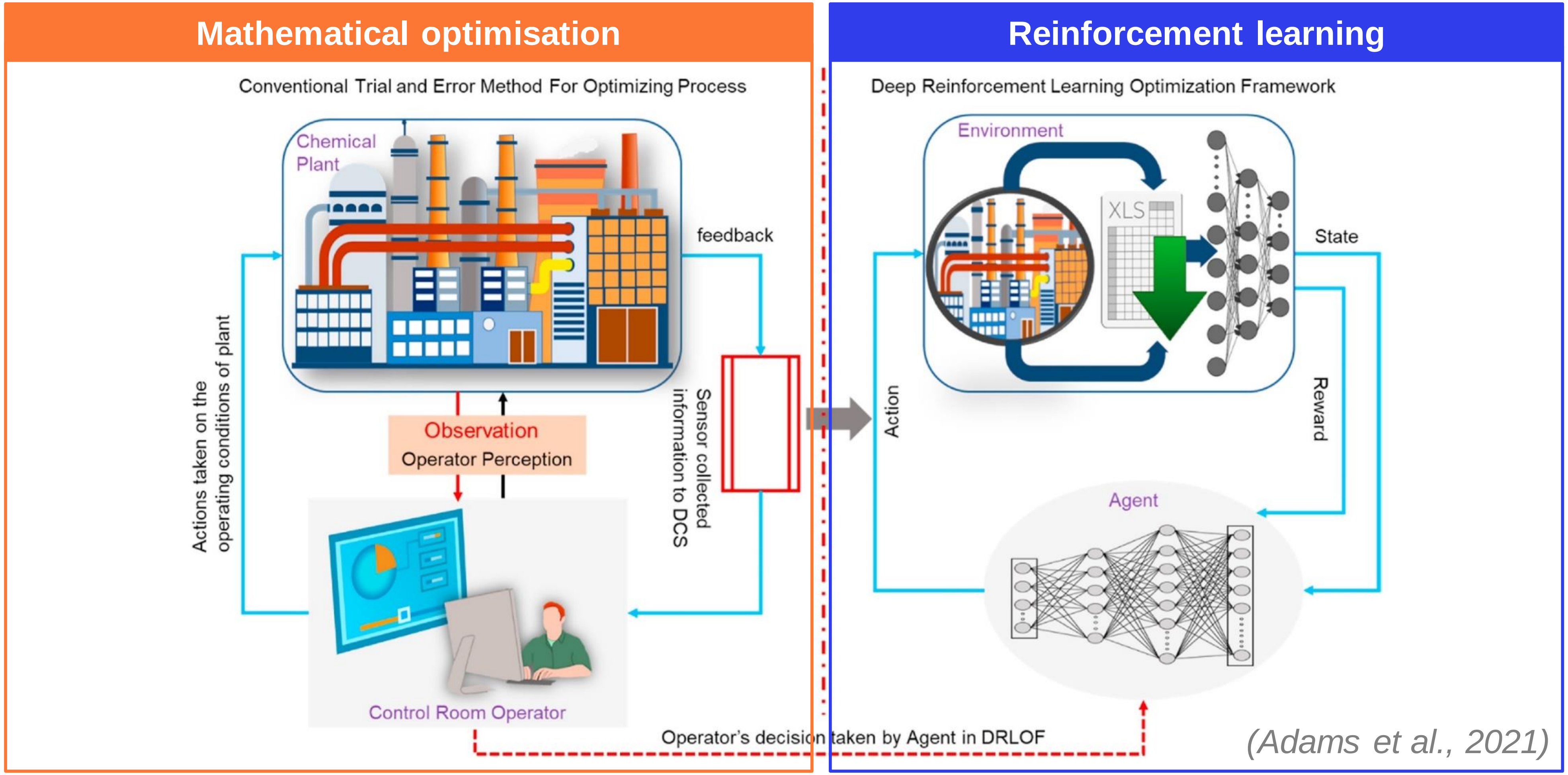

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Case Studies

We applied linear optimisation and reinforcement learning to determine benefits of load flexibility in industrial processes – hydrogen production and datacenter cooling.

Case 1: Chlor-Alkali Electrolysis Process

- **Optimisation modelling** approach
- **Linear Programming/ CPLEX-Solver** (IRPopt framework with perfect foresight)
- Environment engineering modeling (constraints and equations)
- Objective function regarding **costs minimisation** subject to constraints

Case 2: Datacenter Cooling Process

- **Machine learning** approach
- **Model-free Reinforcement Learning / Soft Actor Critic (SAC)** (algorithm that optimizes a stochastic policy)
- State and actions definitions (data-based models)
- **Weighted objective** function regarding **costs and temperature level**
- Action is output of a neural network

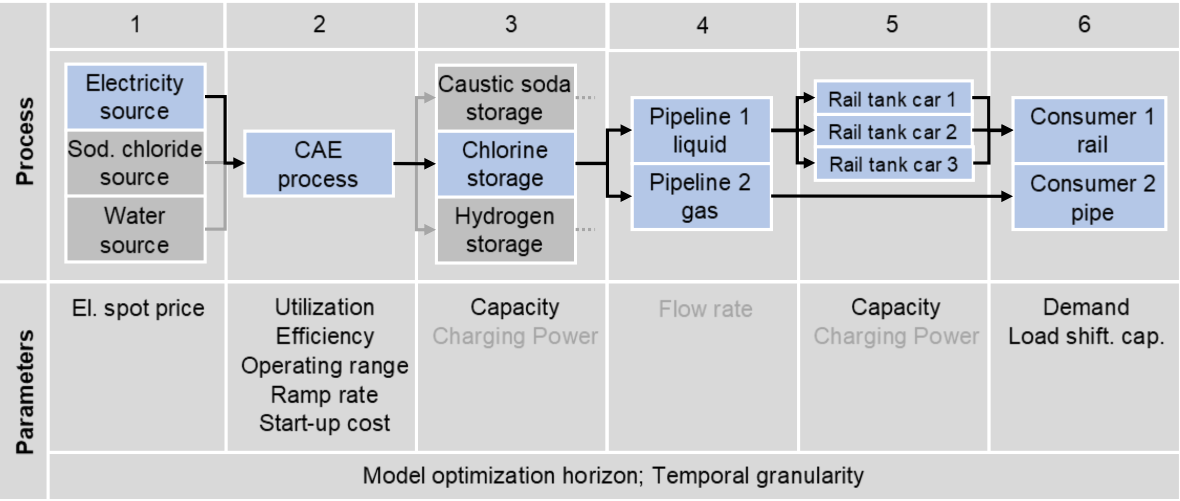
Electricity costs saving potential by applying load shifting / flexible production on real-time prices

- real time electricity prices at the spot market in Germany and Denmark are highly volatile (stochastic) -

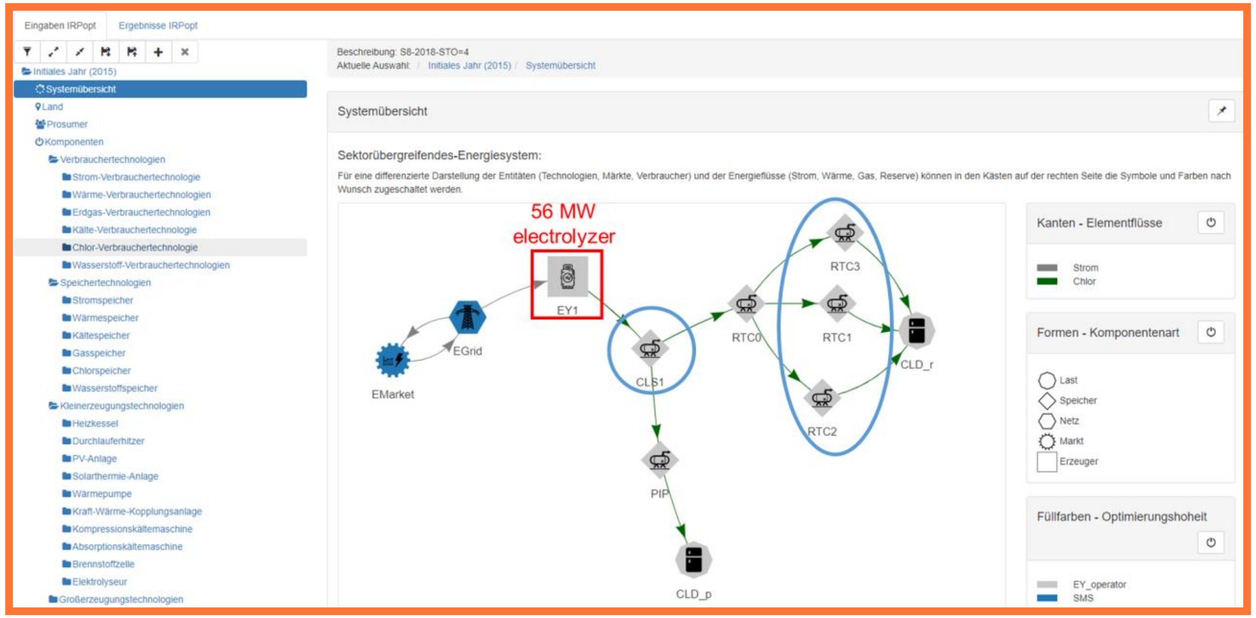
Case 1: Representation

The linear optimisation model IRPopt *(Scheller et al., 2018, 2019)* was used to optimise the procurement costs for electricity in the year 2019 for Germany.

Interlinked physical technologies and processes of the Chlor-Alkali Electrolysis plant



Virtual representation of the Chlor-Alkali Electrolysis plant with the help of the optimisation model IRPopt



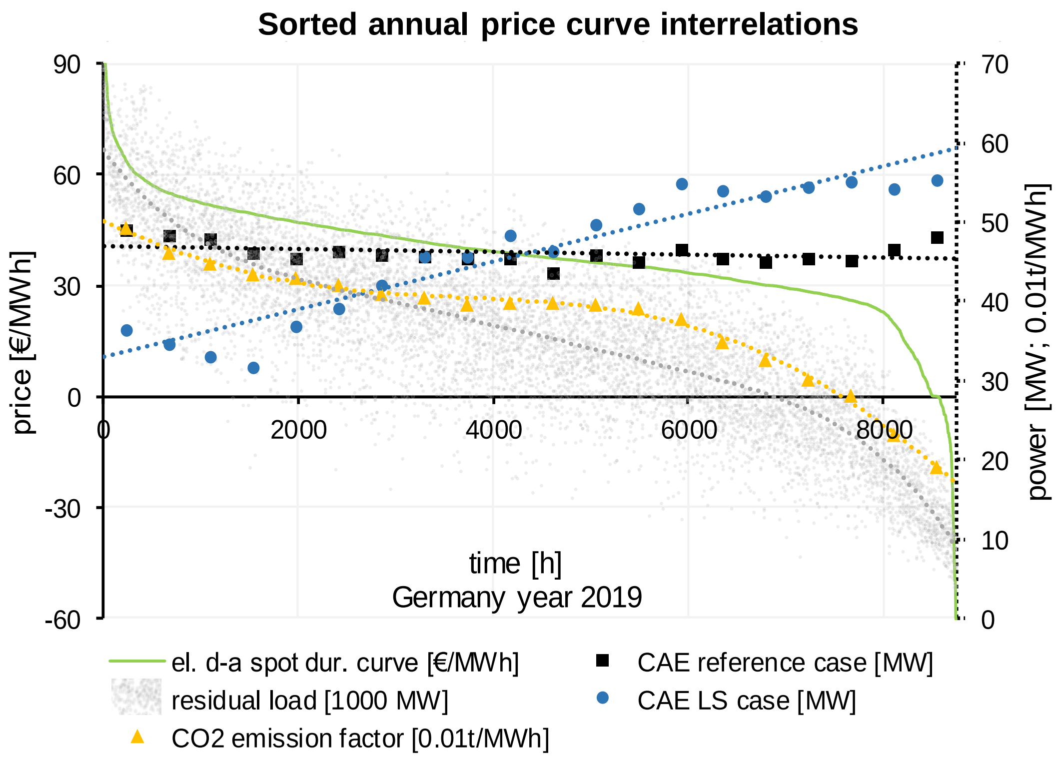
Focus was on the optimal operation of the electroyser process with respect to the electricity prices at the spot market by taking into account the storage, pipeline, and consumer restrictions.

Source: Scheller, Fabian, et al. "Towards integrated multi-modal municipal energy systems: An actor-oriented optimization approach." Applied Energy 228 (2018): 2009-2023. https://doi.org/10.1016/j.apenergy.2018.07.027. Scheller, Fabian, et al.. "Provoking residential demand response through variable electricity tariffs-a model-based assessment for municipal energy utilities." Technology and Economics of Smart Grids and Sustainable Energy 3, no. 1 (2018): 1-20. https://doi.org/10.1007/s40866-018-0045-x.

Case 1: Results I

Operation with load shifting could save ~6% of the electricity costs compared to the actual operation in the year 2019 *(Lerch et al., 2022)*.

- Optimal plant operation leads to **5.8% electricity cost and 2.7% CO² emission savings** compared to actual operation
- Actual operation (black squares) and the electricity prices (green line) are low but positively correlated (0.21)
- Demand Side Management case (blue circular dots) and the electricity prices (green line) are negatively correlated (-0.83)



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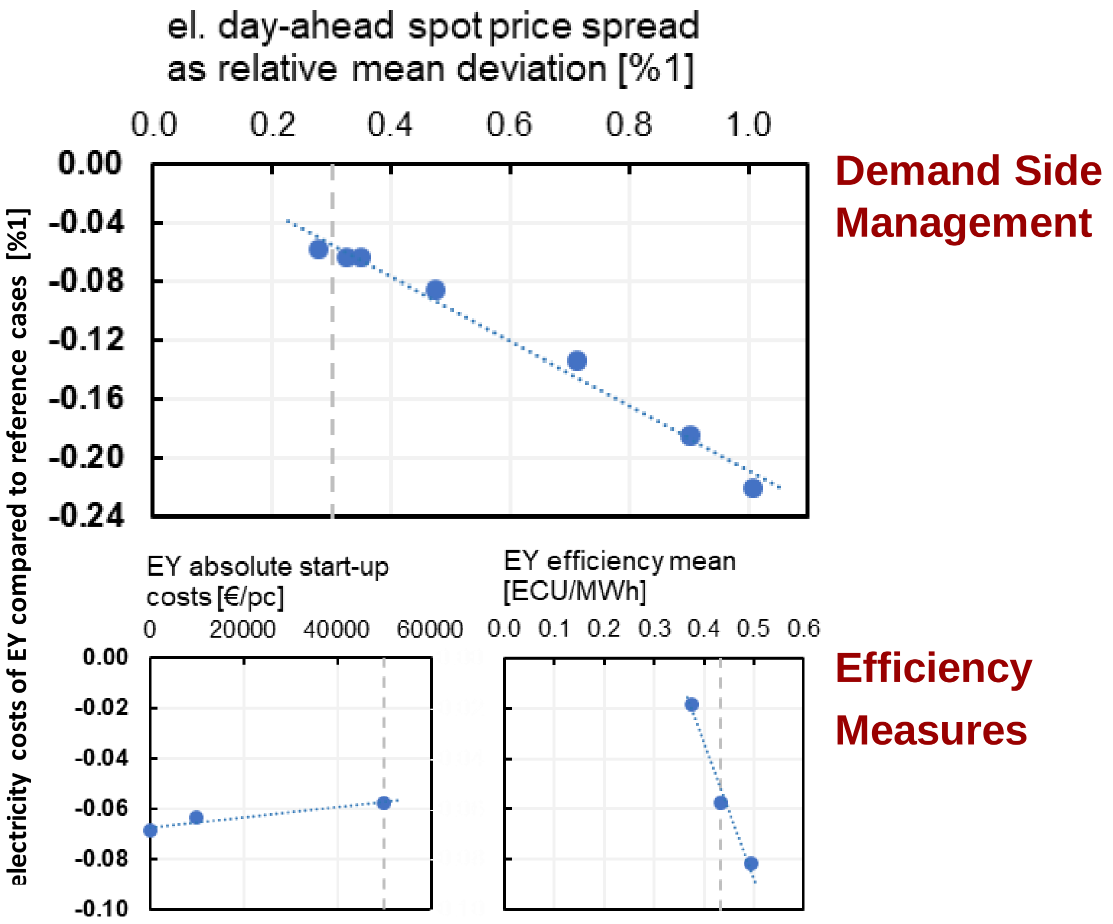
Case 1: Results II

As part of the analysis, we also examined the cost benefits of using load management and efficiency gains *(Lerch et al., 2022)*.

- **Technical increases in efficiency** with regard to the electrolyser (0.43 to 0.49) **result in a cost reduction of approx. 2%**
- **Thermal improvements through waste heat utilization** during start-up (1/3 of the previous costs) result **in cost savings of approx. 0.5%.**

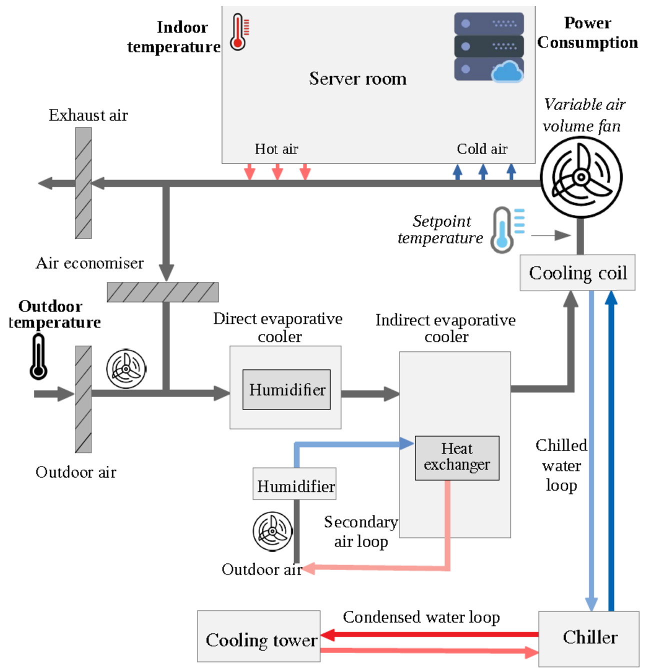


Source: Lerch, Philipp, Scheller, Fabian, David G. Reichelt, and Thomas Bruckner. "Flexibility cost savings potential for chlor-alkali electrolysis plants: a model-based analysis of technical and procedural efficiencies." (to be submitted), 2022.

Case 2: Representation

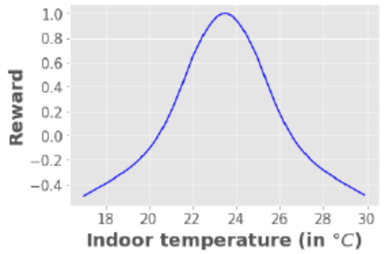
We applied a SAC algorithms with a LSTM instead of a feed-forward network on a simulated two-zone data centre case study of EnergyPlus *(Moriyama et al., 2018)*.

Simplified description of the air loop in the HVAC system of the data centre east zone.



Simulation environment of the virtual agent representation.

Observation Space	Action Space
Outdoor air temperature	West zone temperature setpoint
West zone air temperature	West zone airflow rate
East zone air temperature	East zone temperature setpoint
Total power demand	East zone airflow rate
Power demand of HVAC system	
Intraday Spot electricity price	
Electricity cost	



Reward is: "Gaussian for West zone" + "Gaussian for East zone" - $\lambda \cdot P_{\text{tot}} \cdot p_{\text{elec}}$

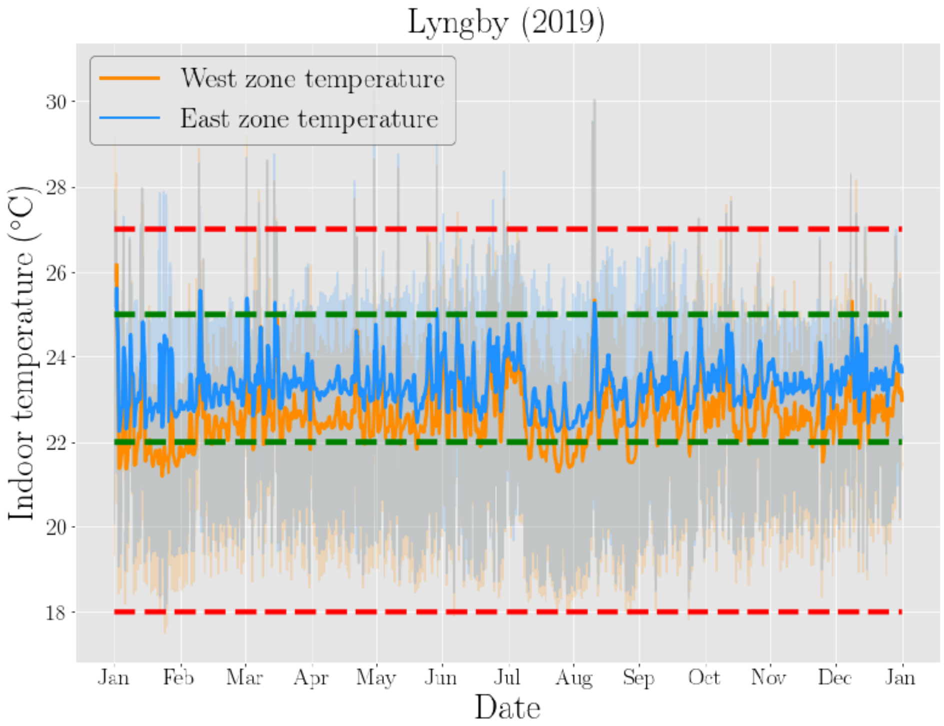
Optimal cooling actions of the agent aimed at maintaining the temperature level in a certain range by simultaneously reducing the electricity procurement costs.

Source: Moriyama, Takao, et al. "Reinforcement learning testbed for power-consumption optimization." In Asian simulation conference, pp. 45-59. Springer, Singapore, 2018. Biemann, Marco, et al. "Experimental evaluation of model-free reinforcement learning algorithms for continuous HVAC control." Applied Energy 298 (2021): 117164. https://doi.org/10.1016/j.apenergy.2021.117164

Case 2: Results I

While there was a cost saving potential of 2% in the year 2019 compared to a PID controller, the SAC algorithm also kept the temperature level *(Biemann et al., 2022).*

- We divided the dataset into training data from 2013 to 2018 and test data for 2019 (spot market data from Denmark)
- **SAC is able to reduce energy costs by 2.2%** compared to a proportional–integral–derivative (PID) controller
- Temperature maintained more or less in the specified range (red line recommended level, green line safety level)
- Price spikes and non-stationarities in the electricity price data were/ are a significant challenge



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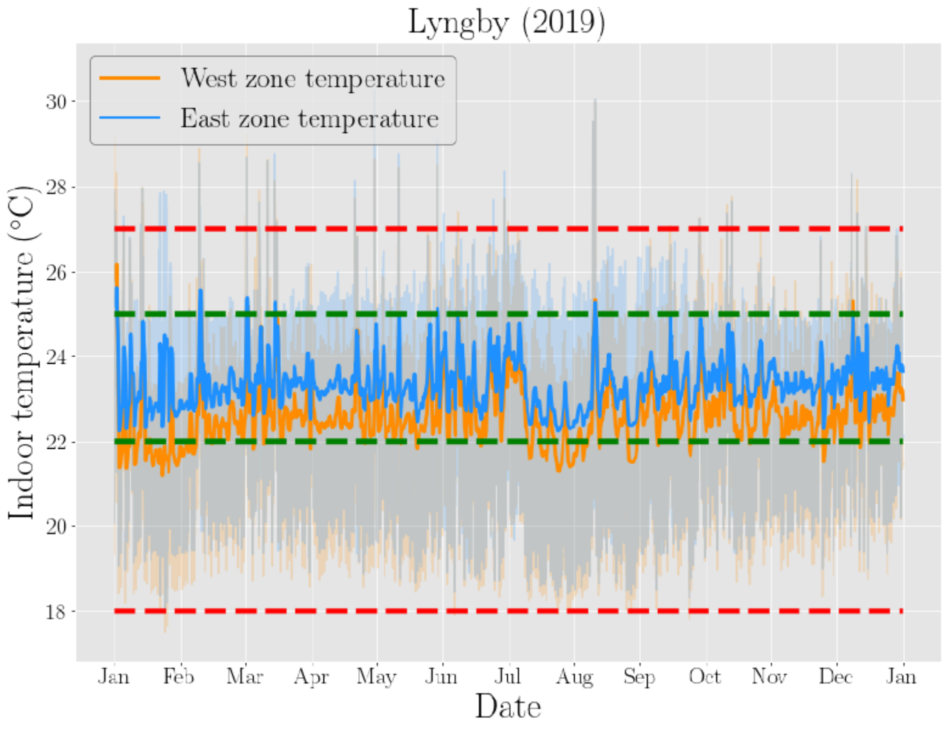
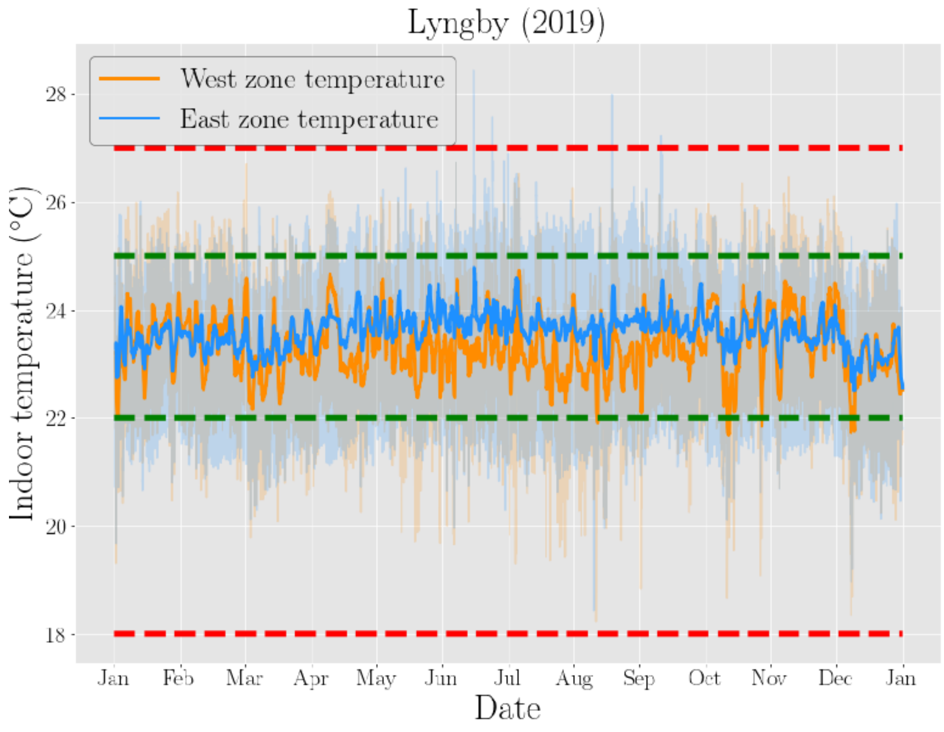
Case 2: Results II

When simply minimising consumption, the algorithm is able to maintain the temperatures in the range quite well *(Biemann et al., 2022).*

Focus on cost reduction



Focus on reduced energy consumption



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Method Selection

Linear optimisation and reinforcement learning frameworks are solving the same problem (and leading to beneficial results), but under different assumptions.

Linear optimisation	Reinforcement learning
✓ Logical problem formulation	✓ Low-level of domain knowledge
✓ Adequate performance	✓ High scalability and adaptability
✓ Safe actions	✓ Decentralised and cooperative coordination
✓ Fluctuation handling	✓ Adequate for complex dependencies
– Centralised decision-making	✓ Fast deployment
– Low adaptability	– Undesirable actions or safety issues
– High-level of domain knowledge	– Data and time demanding training
– Predictions of exogenous variables	– Sim-to-Real problem
– Computational time	– Exception handling

Thank you for listening

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Highlights

- Digital Twins but also Digital Models provide decision-suppport in utilising demand side flexibility for complex industrial environments
- To fully harvest the power of a Digital Twin in optimising the production process in real-time, a fully data-driven and integrated production process is required
- Two industrial case studies demonstrated the benefits of digital support in the industry – the methods linear optimization and reinforcement learning are helpful to assess the potential of load shifting

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