AI for the operational optimization of energy systems: Comparison of data-driven and model-based optimization strategies in power engineering

reducing Energy Costs, CO2 Emissions, Downtime Risks and improving Productivity

16.06.2025 | Dr.-Ing. Niklas Panten | niklas.panten@etalytics.com

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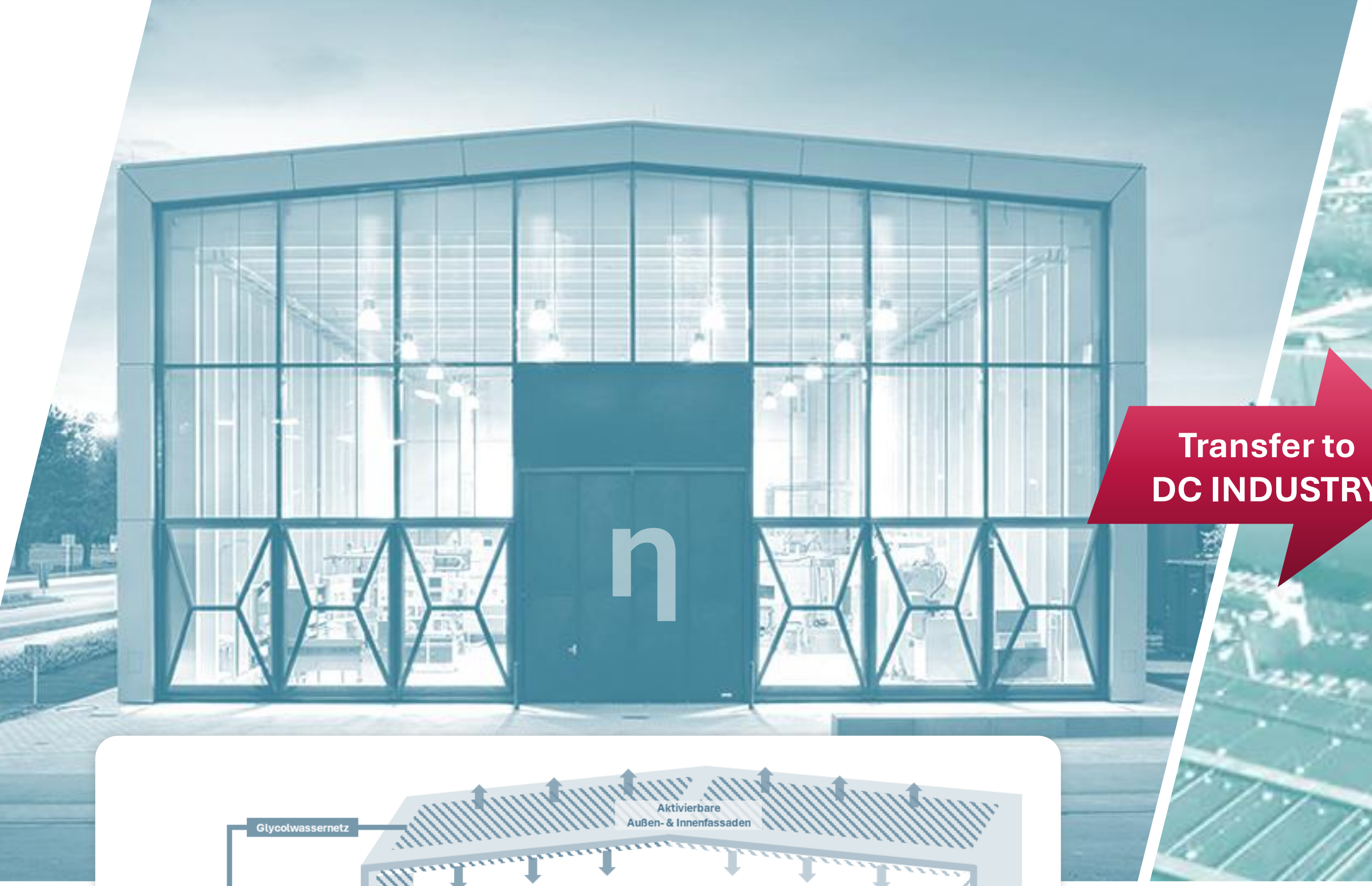
energy intelligence

Agenda

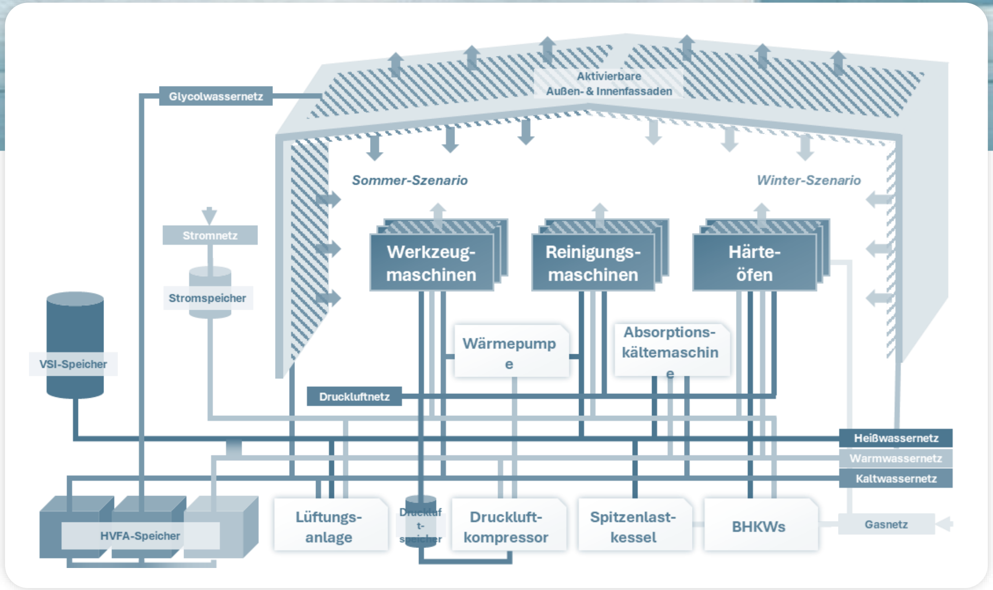
1. Introduction / Context
2. etalytics
3. Deep Dive – Control Optimization: DRL vs. MPC

ETA Research Factory @ TU Darmstadt



Equinix FR6

Transfer to DC INDUSTRY

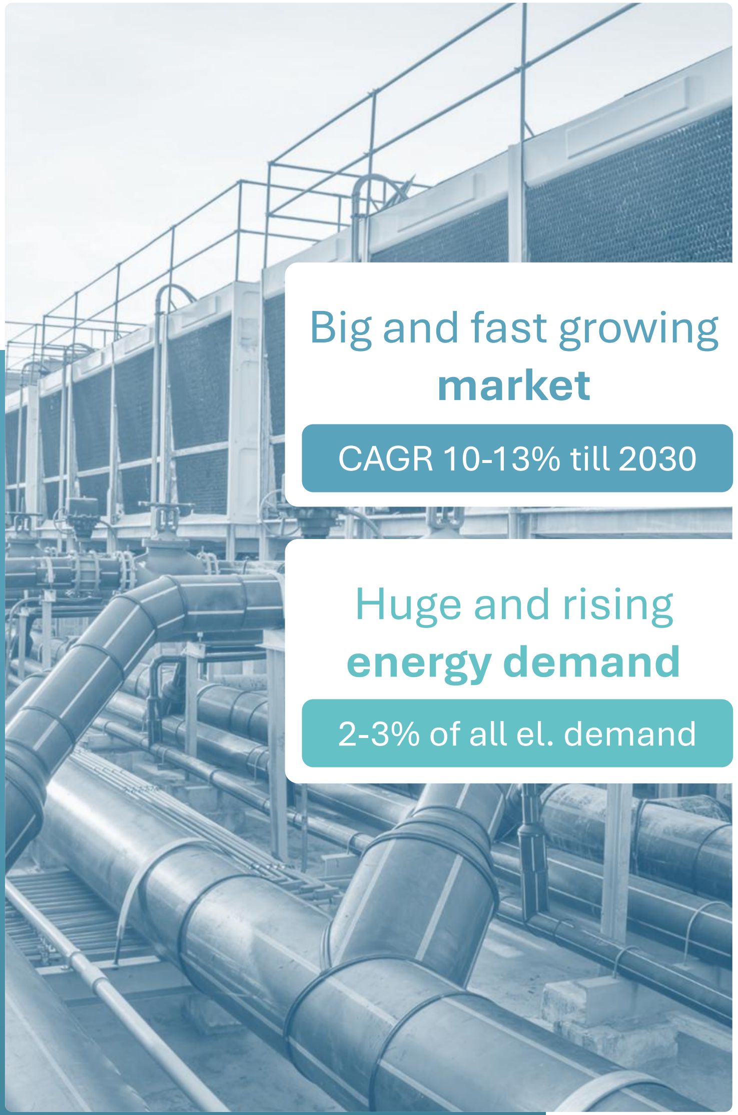


10+ Years of Research & Industry Experience to Solve the Puzzle

We combined Energy Science, Engineering and Computer Science / AI and applied it on Large-Scale Industrial Energy Systems.

The Unsustainable Energy Hunger of Data Centers

Facing the Challenges of Rapid Sector Growth

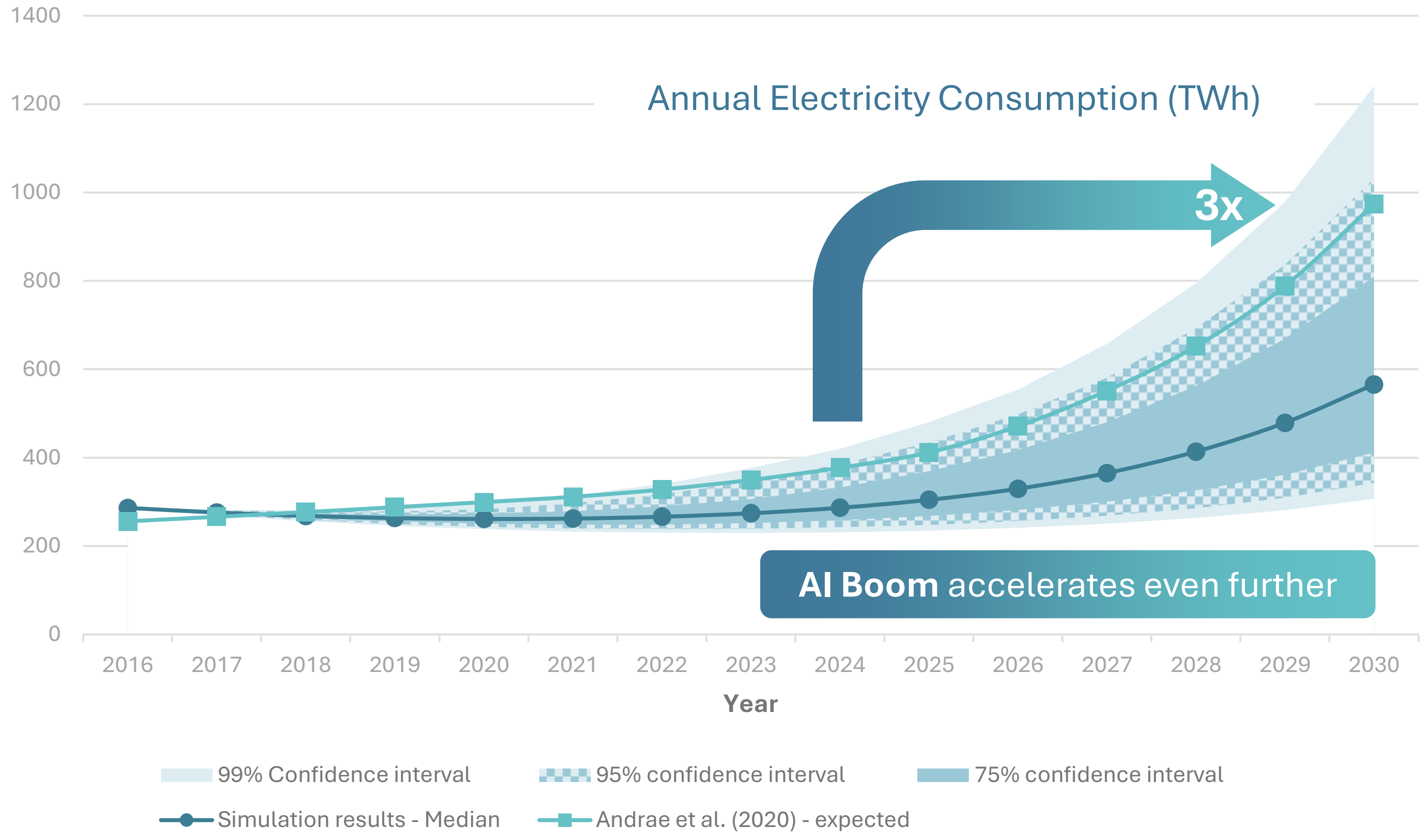


Big and fast growing **market**

CAGR 10-13% till 2030

Huge and rising **energy demand**

2-3% of all el. demand



Koot, M., & Wijnhoven, F. (2021). Usage impact on data center electricity needs: A system dynamic forecasting model. Applied Energy, 291, 116798. https://doi.org/10.1016/j.apenergy.2021.116798

Mastering the Energy Symphony

Orchestrating Systems for Peak Performance

Why Data Center Cooling is Challenging and often Inefficient

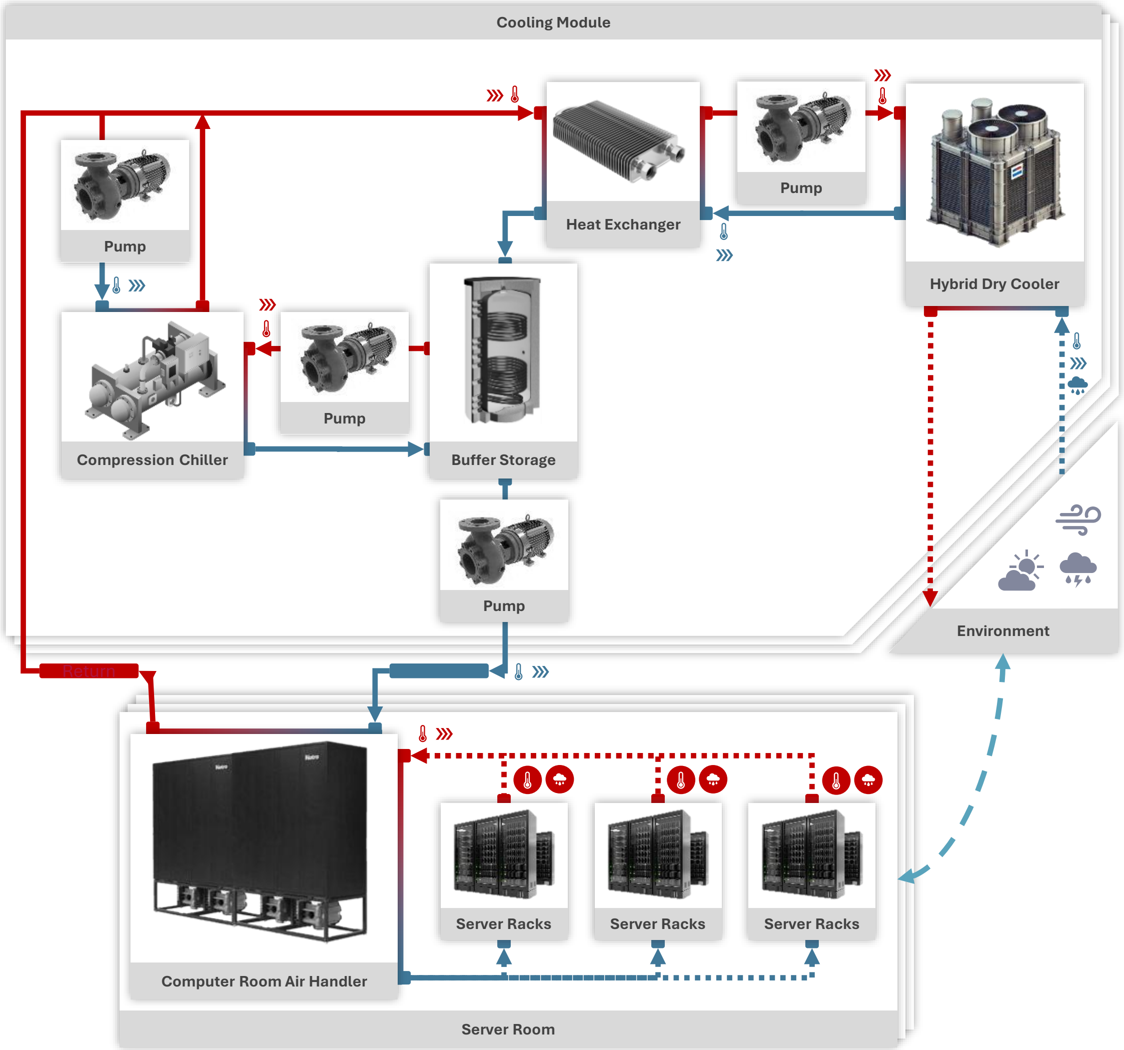
Holistic optimization needs the perfect and predictive orchestration of all energy converters involved

- Complex Topologies
- Huge Control Space
- Diverse Interdependences
- Dynamic Influences

In a **Critical Infrastructure** Environment with **fewer staff**

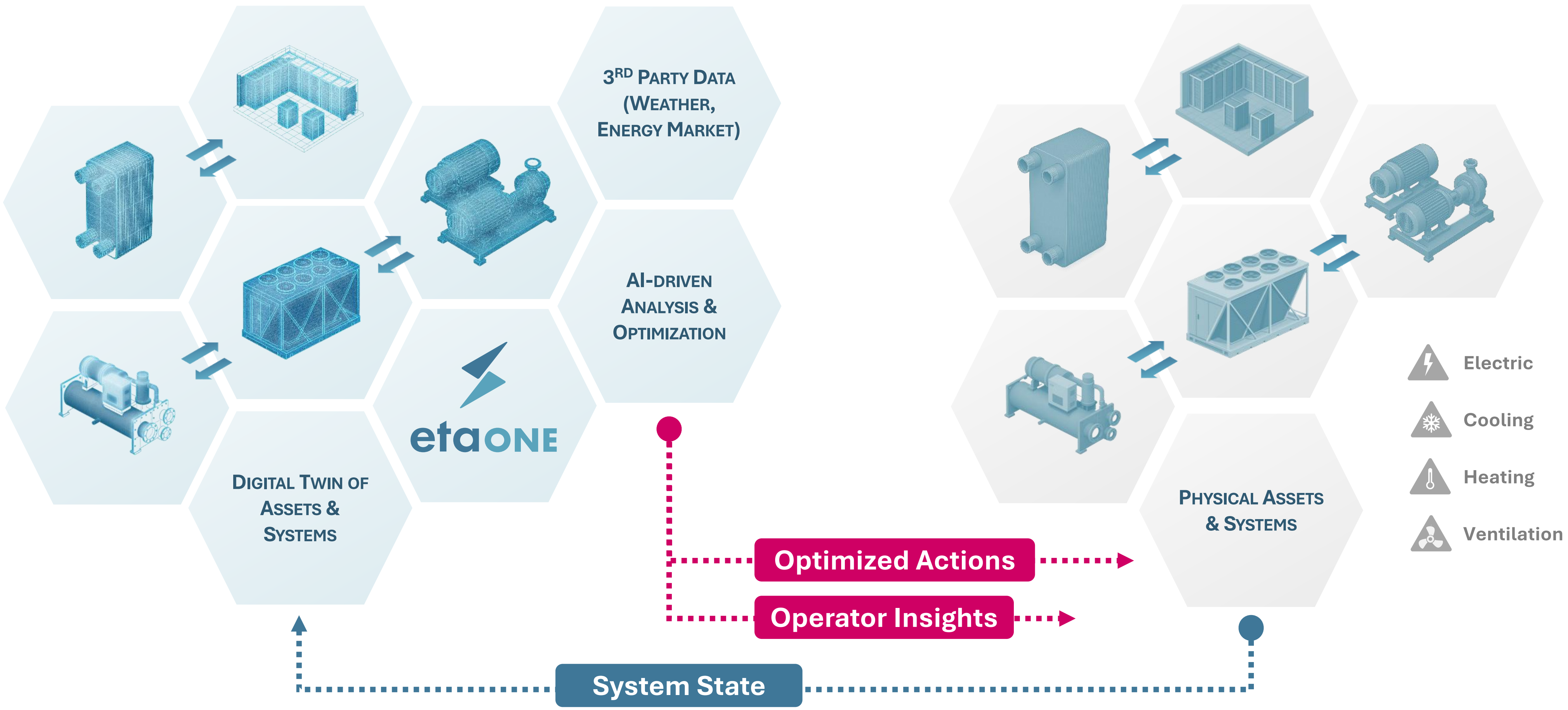
How to...

- ✓ MAXIMIZE UPTIME ?
- ✓ MEET SUSTAINABILITY GOALS ?
- ✓ PASS COMPLIANCE AUDITS ?
- ✓ AND PROTECT EQUIPMENT ?



etaONE® — Your Energy Intelligence Layer

Built on physics. Trained on your data. Designed for your energy system and BMS.



Real Results at Scale – Trusted by Global Data Center Leaders

From One Site to a Global Footprint

EQUINIX FR6, Frankfurt

6.600 m^2 IT-SPACE | 3.000 CABINETS | 2017 CONSTRUCTED

49,3 % Energy Savings (in scope)

>900 MWh/a Energy Reduction

>240 tCO_2/a CO_2 Emissions Reduction

<1 year Amortization Period

JENS-PETER FEIDNER

Managing Director, Equinix Germany

“*Since implementing etalytics, we've seen a measurable reduction in energy consumption. The platform's ability to dynamically optimize our setpoints has directly contributed to our **cost savings and emissions reductions without compromising performance**.*

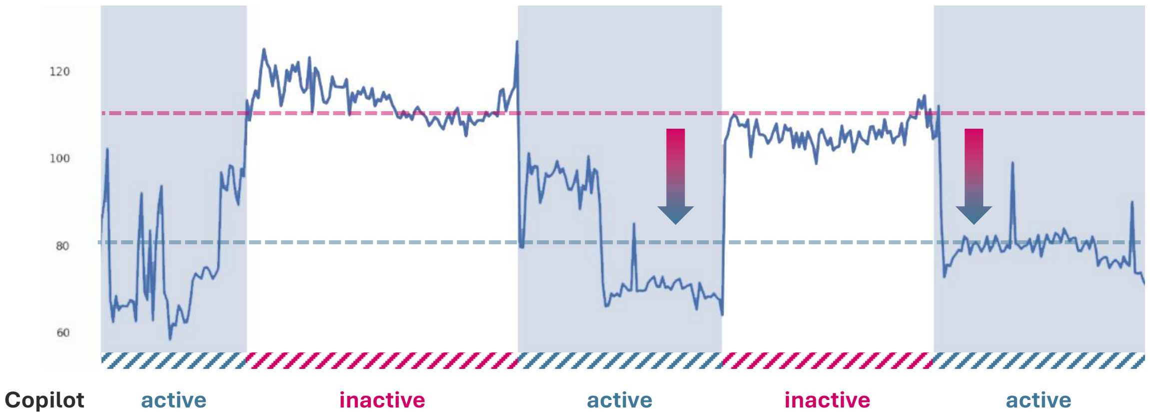
*The platform's safety protocols and fail-safes give us confidence that even though we're using AI, we **maintain full control** and ensure our infrastructure's integrity.*

We've always felt supported by etalytics—whether it's through training, troubleshooting, or optimizing the system. They truly understand the needs of critical infrastructure.

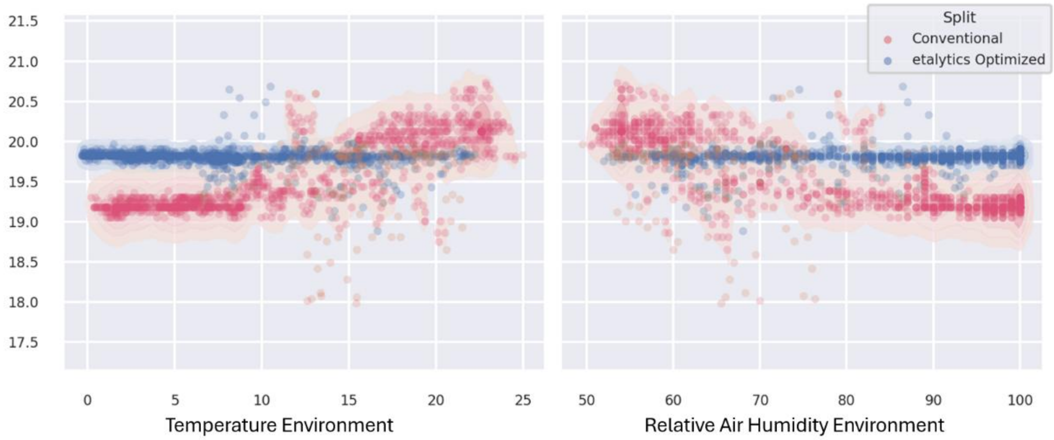
Beyond Savings: What AI-Driven Control Feels Like

More stability. More awareness. Less manual stress.

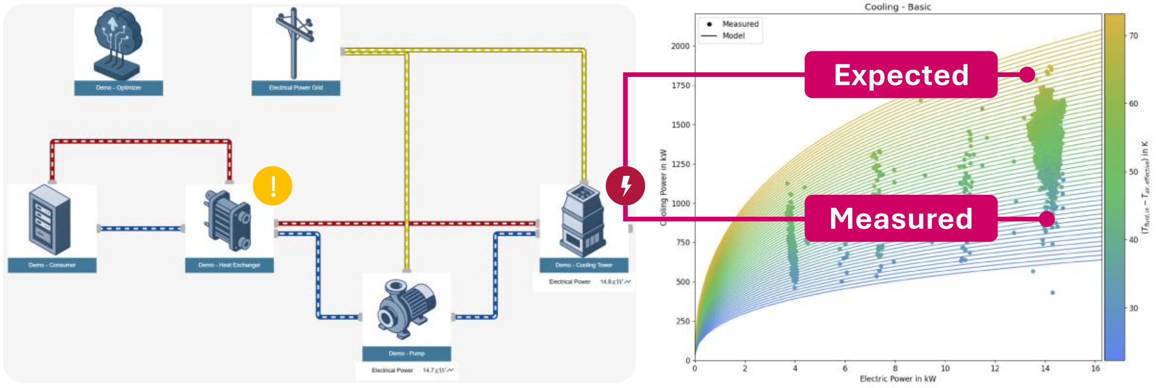
Lower power / energy / runtimes & wear / costs



More stable supply temperatures / SLAs



Transparency, preventive alarms & situational awareness



> “Whether you’re building new or optimizing old, AI is becoming the new standard in operational excellence.

Your Trusted Innovation Partner in Energy Intelligence

Our solutions create impact across industries and applications.

Electric | Cooling | Heating | Ventilation — Horizontal Applications

Industry Verticals:

- **Data Centers**: Equinix, Digital Realty, NTT
- **Automotive**: VW, Audi, Stellantis
- **Chemical / Health**: Grünenthal, Merck, Sanofi

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>60 | 120*
Employees | *2026

Frankfurt a.M., DE
Headquarters

San Francisco, CA
US Office

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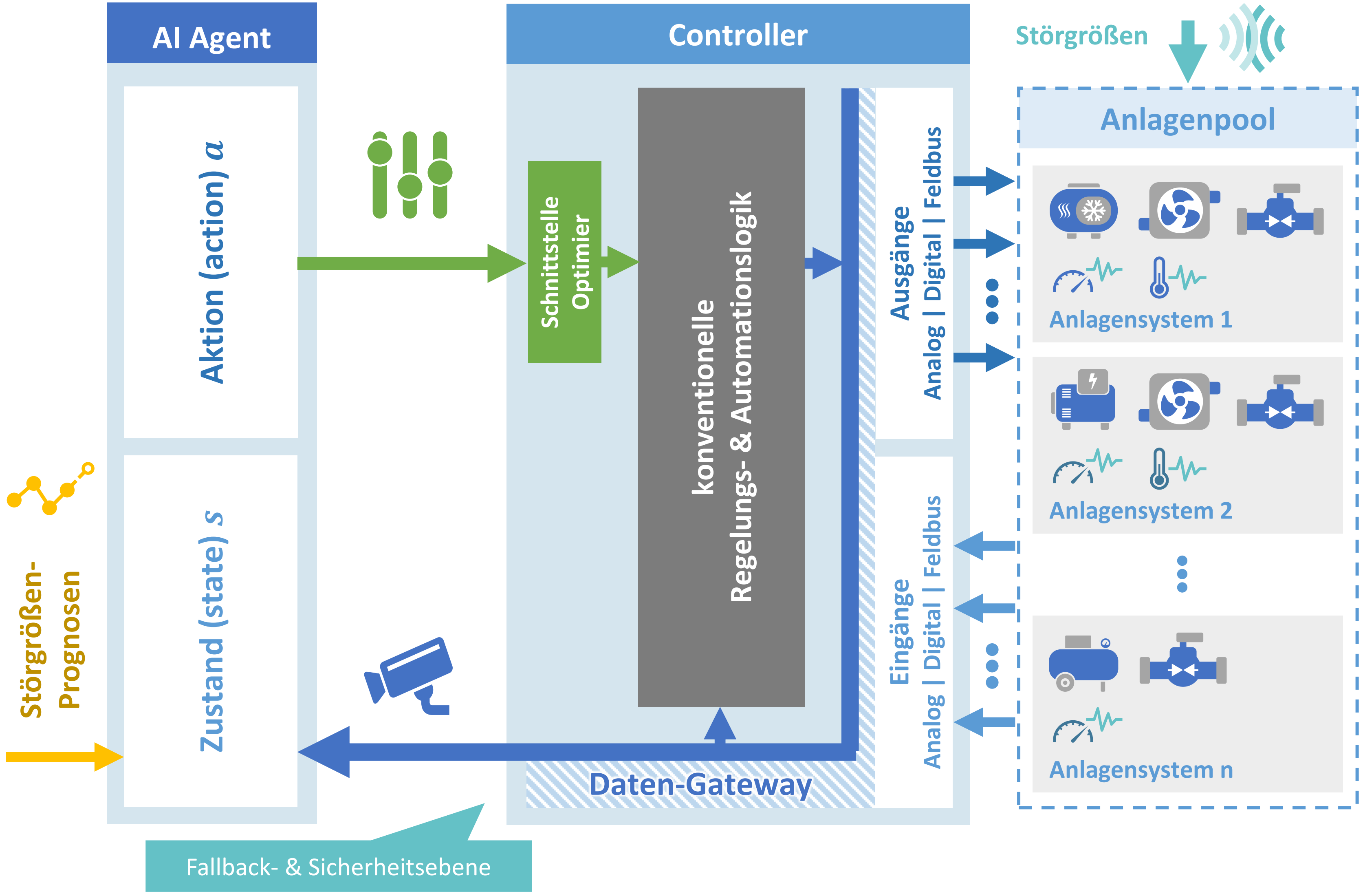
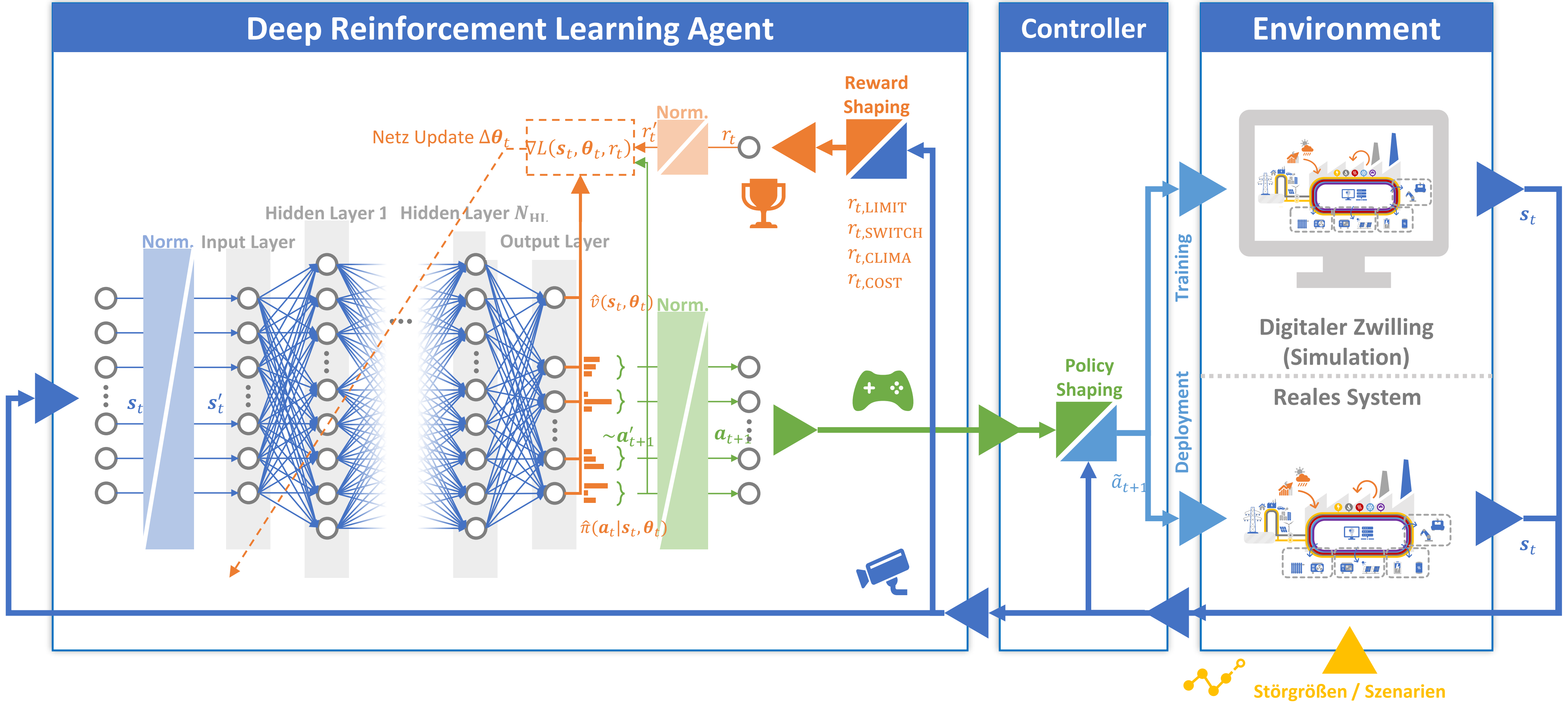
Understanding AI Optimization of Industrial Energy Systems

A Deeper Dive

AI Copilot Addon for Energy System Control



Actor-Critic DRL Control



1 Für Iterationen und mehrere Umgebungen Samples generieren $a \sim \pi(a_t|s, \theta)$

2 Mit Sequenzen diskontierte Erträge berechnen

3 Sequenzen durchmischen und in Mini-Batches aufteilen

4 Update der Netzparameter gemäß zu maximierender Zielfunktion

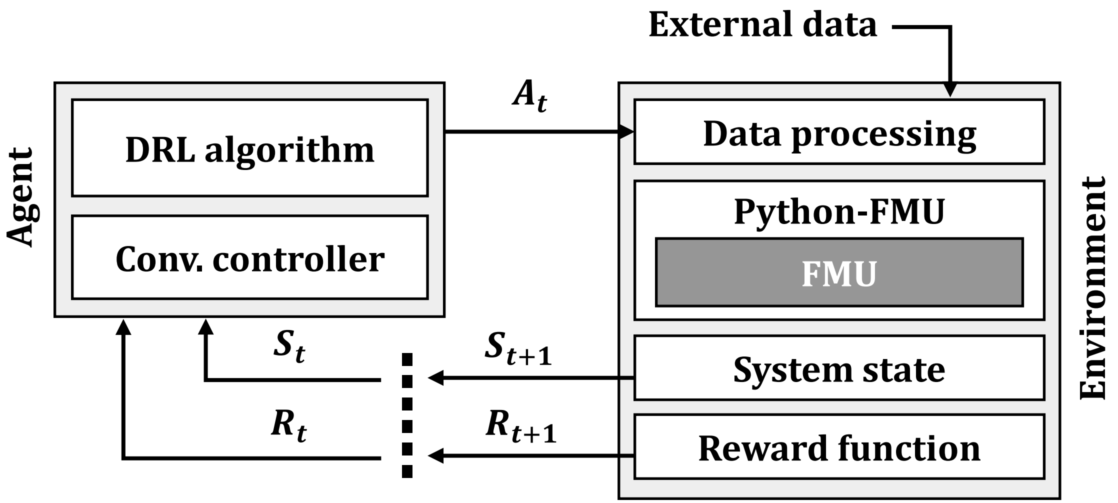
Application Case

Bosch Rexroth Schweinfurt – framework and DRL implementation

Weigold et al.: Method for the application of deep reinforcement learning for optimised control of industrial energy supply systems by the example of a central cooling system

2 … framework and validation

3 Implementation of DRL algorithm



DRL algorithm

- Proximal policy optimisation (PPO)
- Neural network topology: MLP
- Hyperparametertuning
- Training phase

Reward function

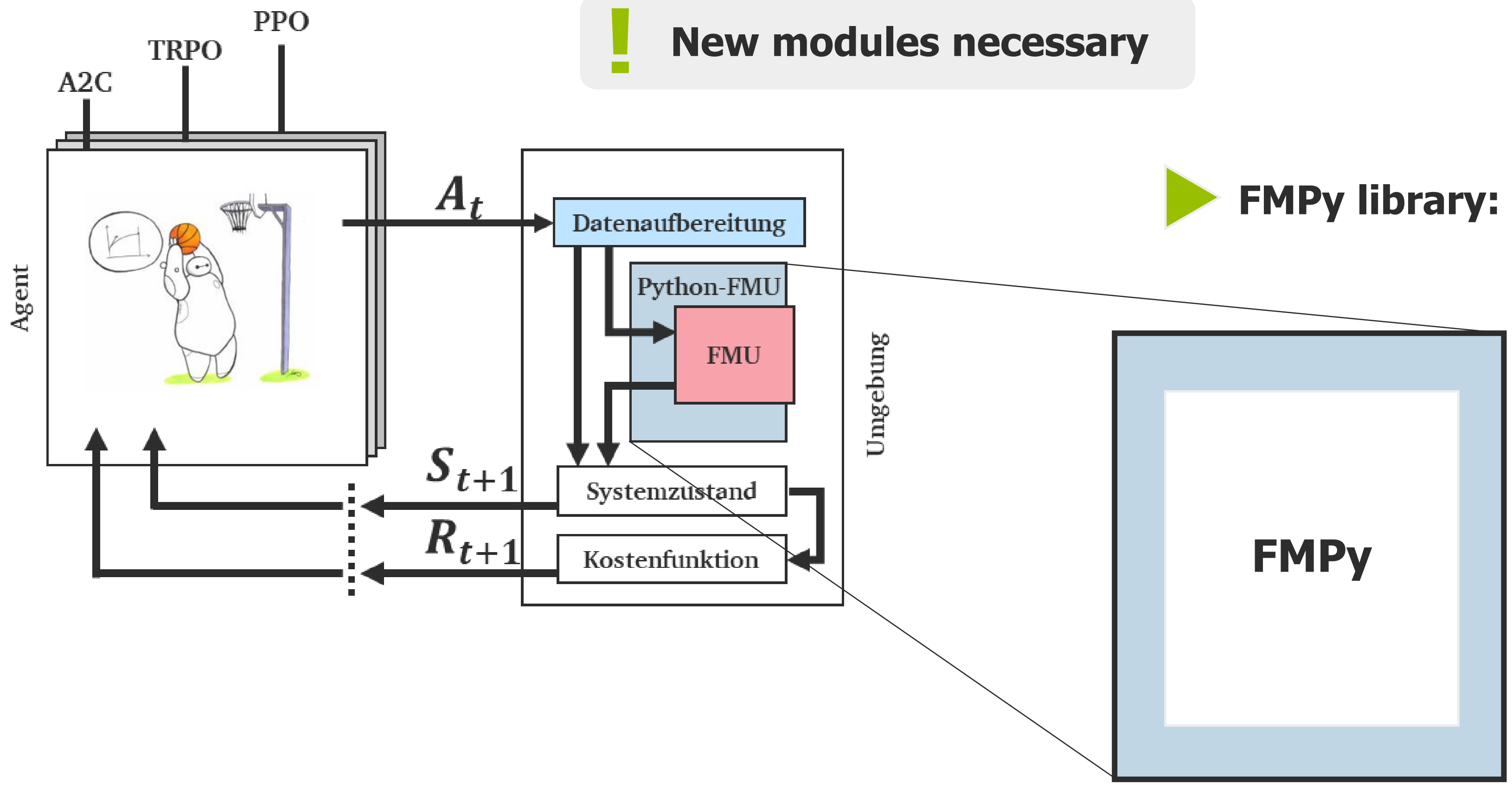
Weighted sum of individual costs

$$R_t = \underline{w_T K_T} + \underline{w_E K_E} + \underline{w_S K_S} + \underline{w_O K_O}$$

Implementation

Creating an Python-FMU interface that is compatible to the Gym-Structure

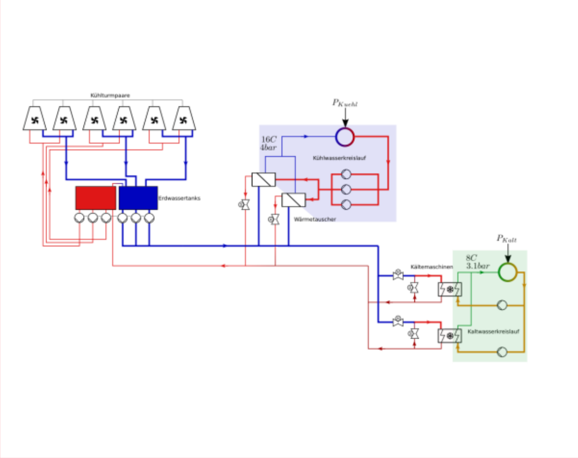
! New modules necessary

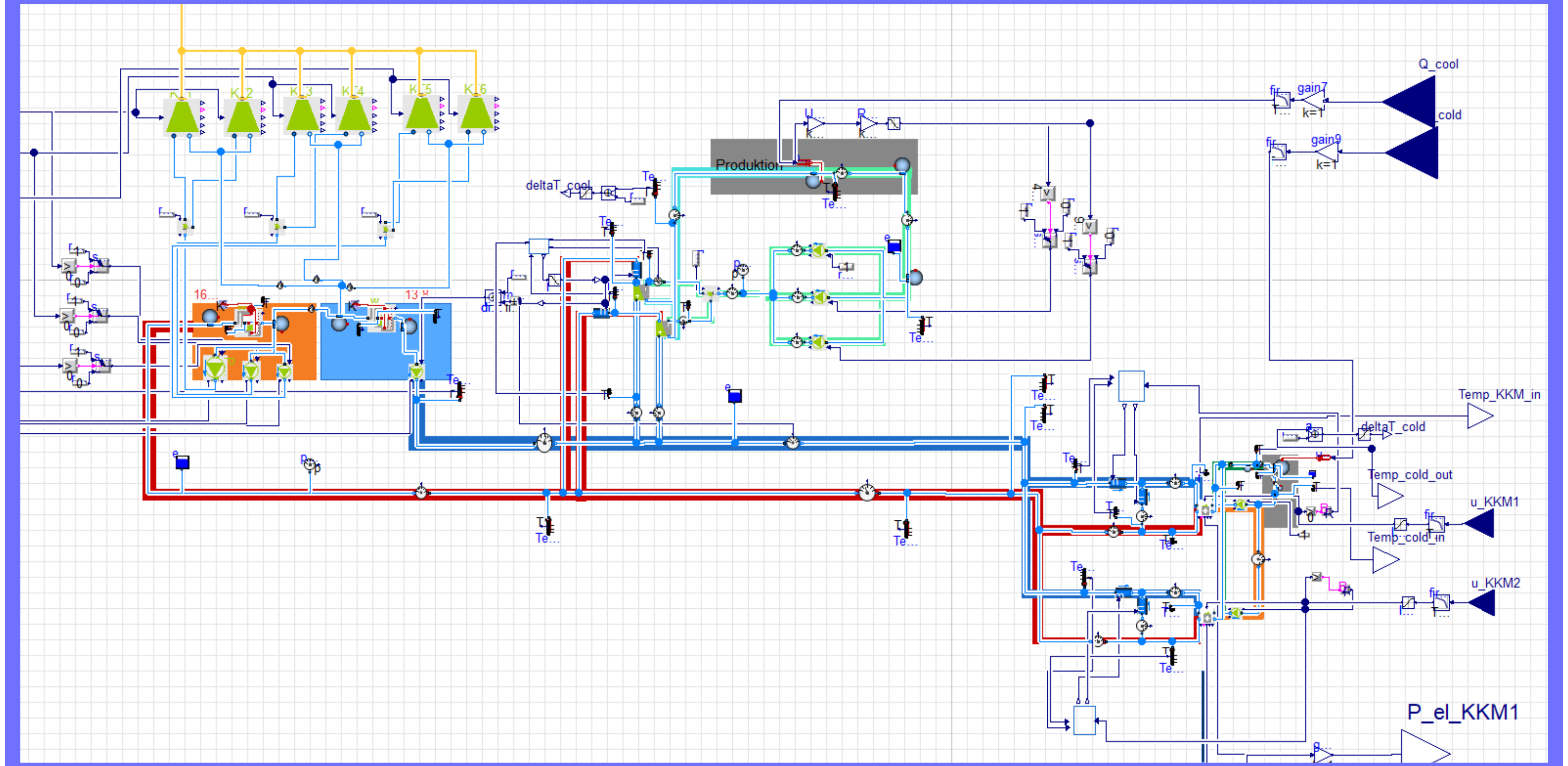


- **FMPy library:** https://fmpy.readthedocs.io/en/latest/

Implementation

Build a Simulation of the supply systems and export it as an FMU





Visit our tutorial: click here

Reward-Design

Ökonomische Reward-Funktion erweitert mit Straftermen

$$r_t = r_{t,\text{costs}} + r_{t,\text{switches}} + r_{t,\text{limits}} + r_{t,\text{others}}$$

1

Energiekosten r_{costs}

RTP Demand-Response Modell (Dynamische Preise)

$$= -C_{\text{E,el}}(\text{t}) - C_{\text{E,gs}}(\text{t}) - C_{\text{E,tx}}(\text{t}) - C_{\text{el,P}}(\text{t})$$

- Energiebezug (Strom, Erdgas)
- Steuern und Umlagen
- Elektrische Lastspitzen (Netzentgelte)

2

Schaltvorgänge r_{switches}

$$= -\sum_{i \in D} \begin{cases} c_{\text{switches},i}, & b_{\text{on,off},i}(t) \\ 0{,}1 \cdot c_{\text{switches},i} \cdot |s_{u,i}(t) - s_{u,i}(t-1)|, & \text{sonst} \end{cases}$$

3

Grenzwerte r_{limits}

$$= c_{\text{limits,c}} \cdot \left(\varphi\left(\vartheta_{\text{c,min}} - \vartheta_{\text{c}}(t)\right) + \varphi\left(\vartheta_{\text{c}}(t) - \vartheta_{\text{c,max}}\right)\right) + \cdots$$

$$c_{\text{limits,h}} \cdot \left(\varphi\left(\vartheta_{\text{h,min}} - \vartheta_{\text{h}}(t)\right) + \varphi\left(\vartheta_{\text{h}}(t) - \vartheta_{\text{h,max}}\right)\right) + \cdots$$

$$c_{\text{limits,r}} \cdot \left(\varphi\left(\vartheta_{\text{r,min}} - \vartheta_{\text{r}}(t)\right) + \varphi\left(\vartheta_{\text{r}}(t) - \vartheta_{\text{r,max}}\right)\right) + \cdots$$

$$c_{\text{limits,ax}} \cdot \varphi\left(n_{\text{ax,min}} - n_{\text{ax}}(t)\right)$$

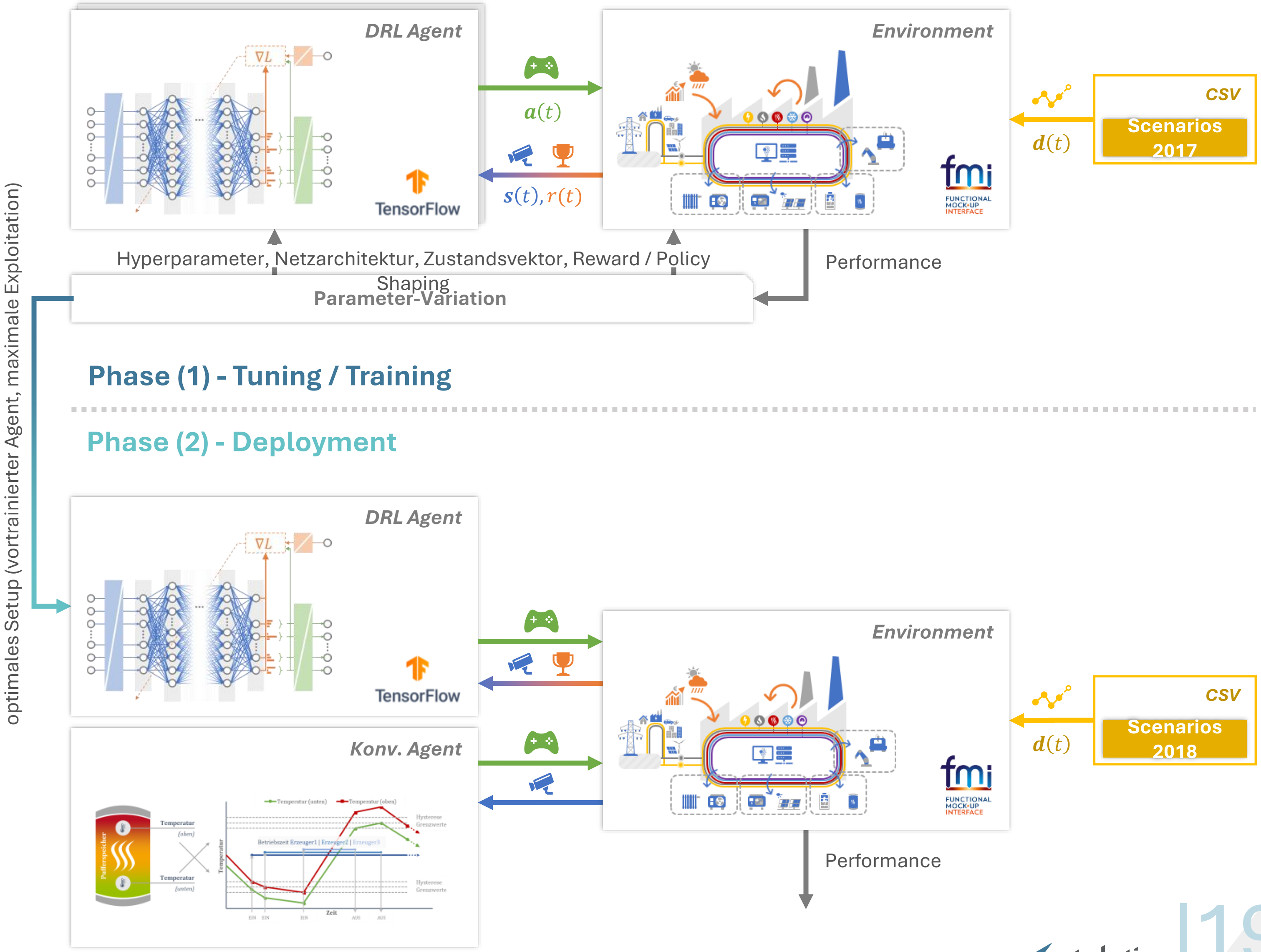
4

Weitere r_{others}

$$= \underbrace{I_{\text{Bat}} \cdot \left(\frac{SoH_{\text{Bat}}(t-1) - SoH_{\text{Bat}}(t)}{0{,}2}\right)}_{c_{\text{age,Bat}}} + \begin{cases} c_{ps}, & \text{Policy-Shaping aktiv} \\ 0, & \text{sonst} \end{cases}$$

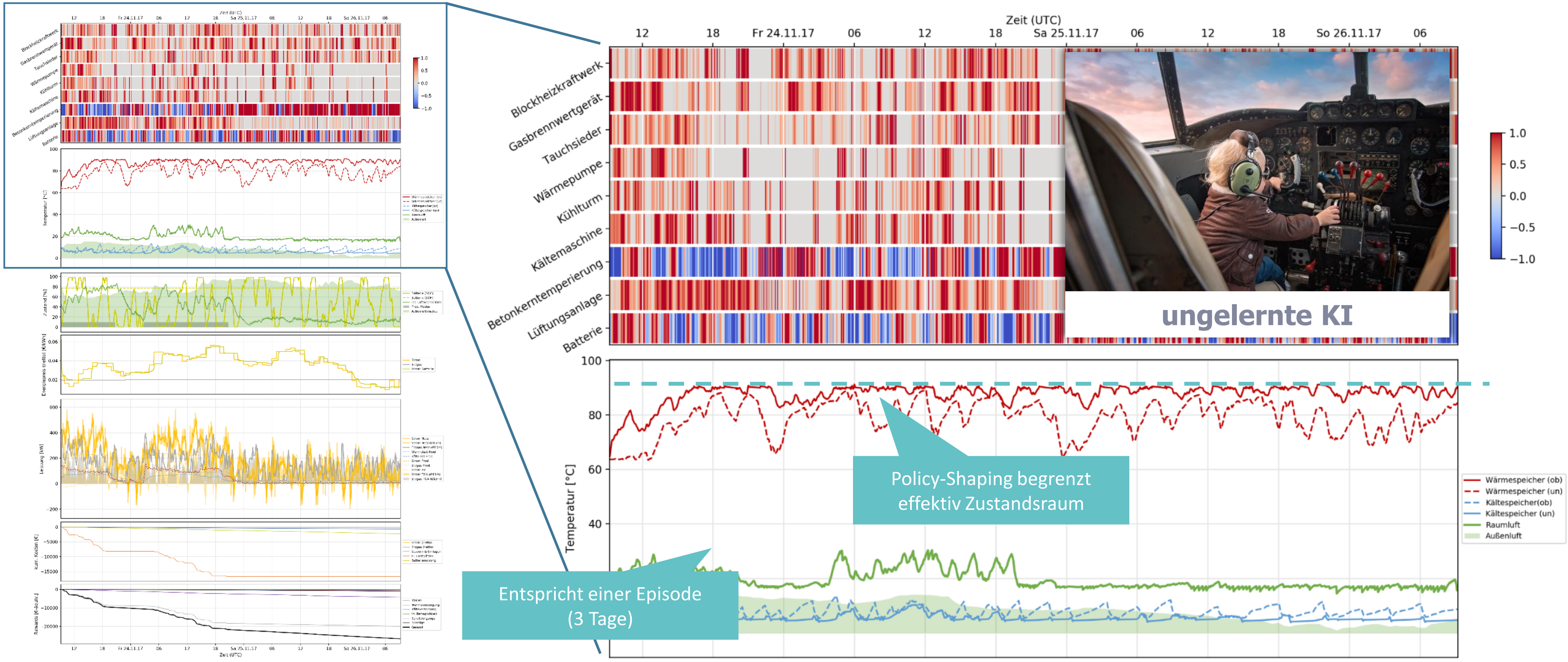
Evaluierung in zwei Phasen

- Tuning / Training auf Szenario 2017 Daten
- Letztendliche Erprobung auf 2017 sowie unbekannten 2018 Daten, um ggf. zu gute Ergebnisse durch Overfitting zu vermeiden
- Vergleich zu konventioneller Regelung umgesetzt als Agent im Framework



KI bei „Exploration“ des State & Action Space

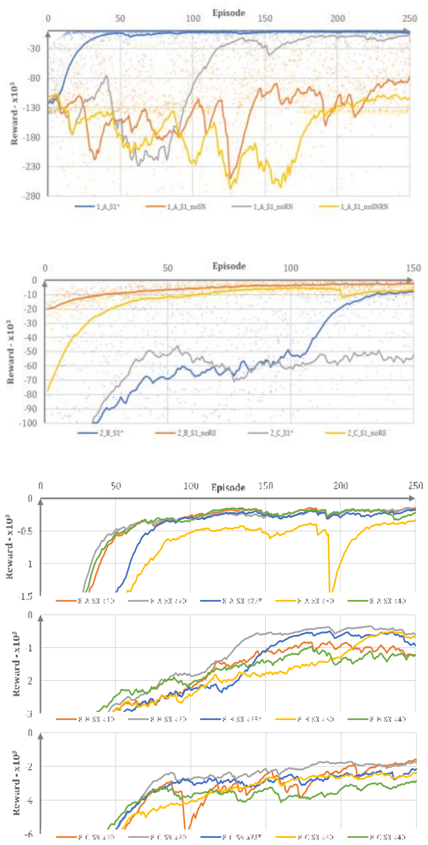
Algorithmus erkundet Zustands- und Aktionsraum mit jeweiligen Belohnungsgrößen

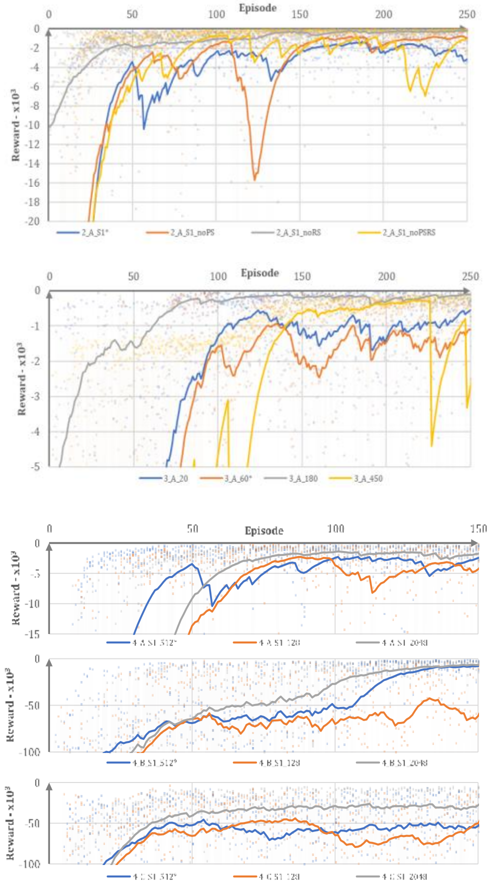


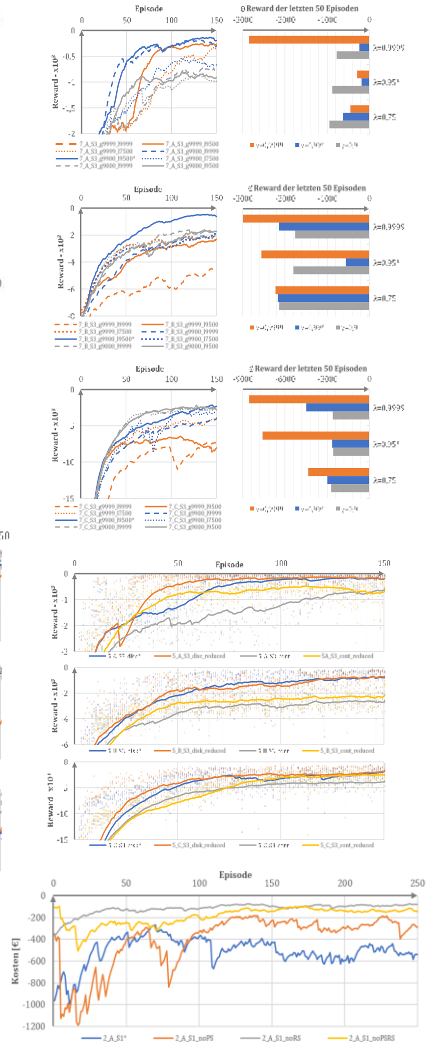
Parameter-variationen und Versuche

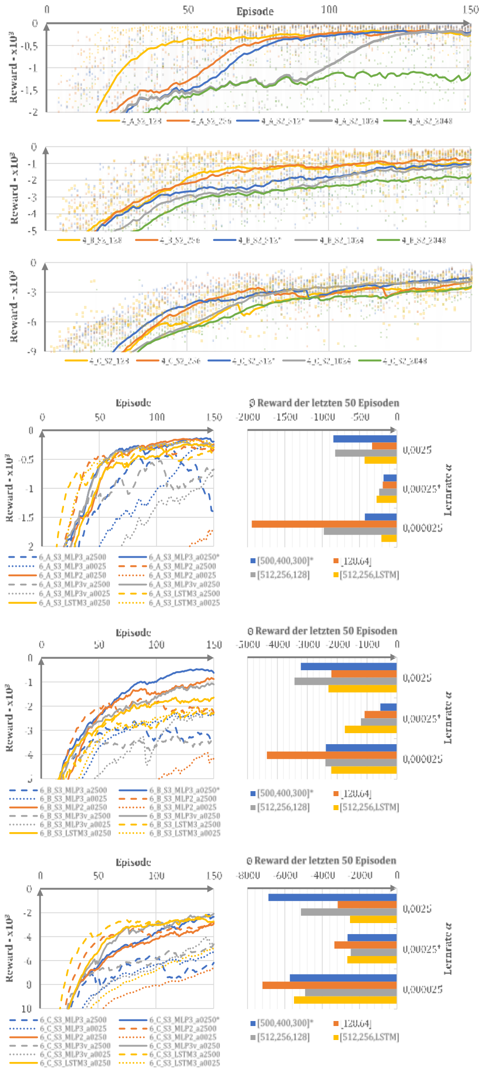
Umfangreiche Evaluierung unterschiedlicher Hyperparameter-Setups für Algorithmus, Reward- und Policy-Shaping sowie bei Mod

TECHNISCHE UNIVERSITÄT DARMSTADT









>2 Mrd. Datensätze

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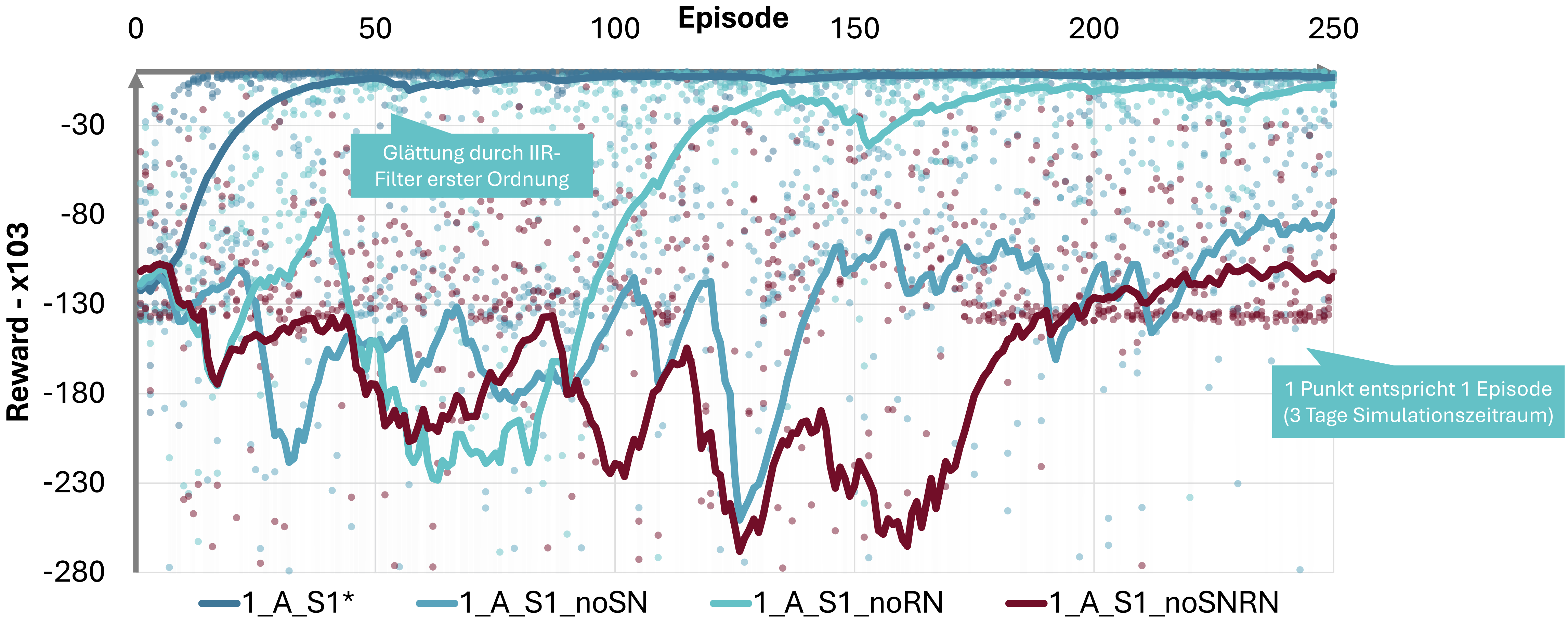

Trainingsfortschritt über Episoden

Konvergenz gegen (lokales) Optimum bei geeigneter Parametrierung des Verfahrens

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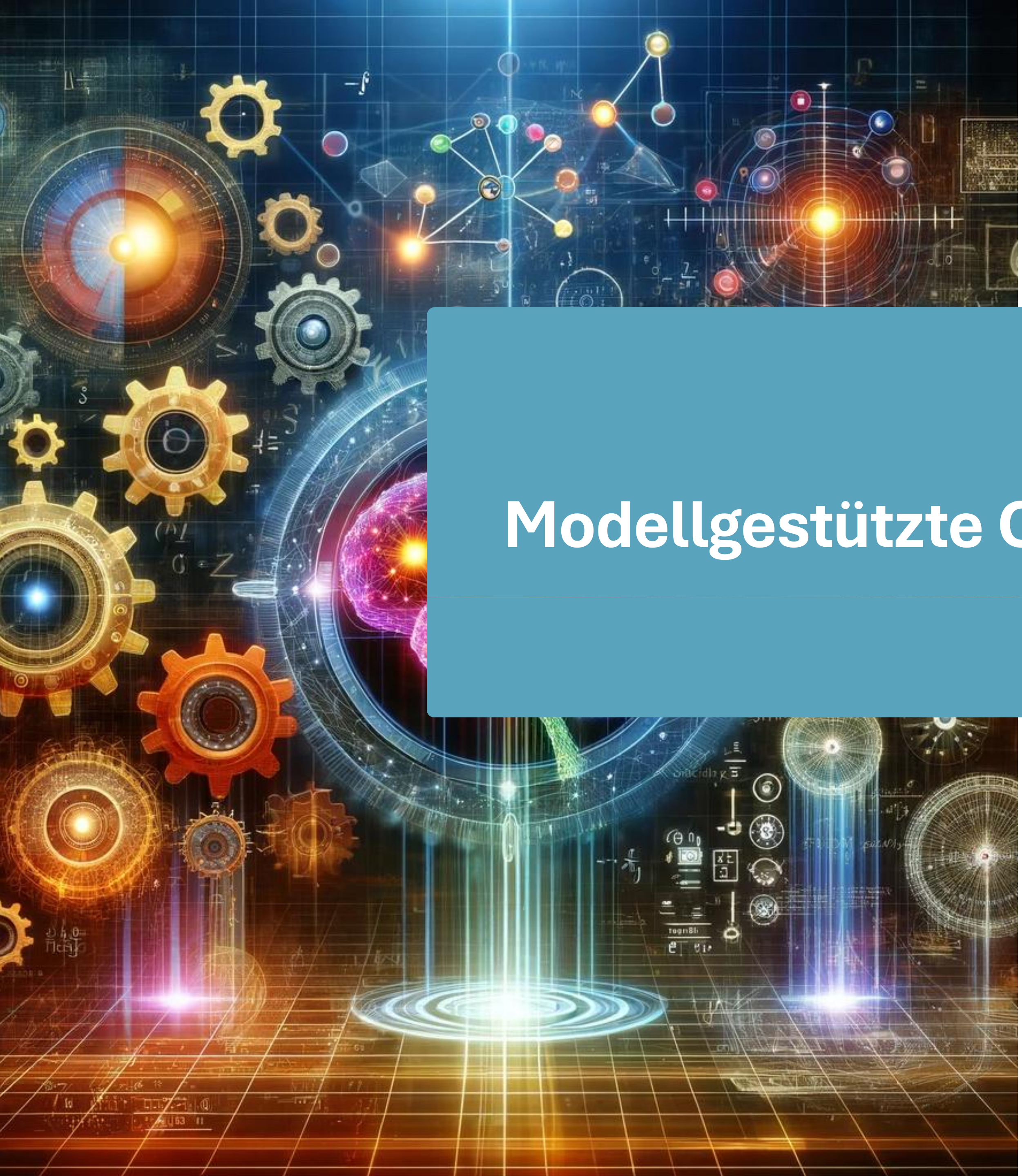
Kritische Diskussion des Verfahrens

Zusammenfassung der Evaluation von funktionalen und formalen Anforderungen

- Konvergenz für komplexe Energiesystem
- Einfach anpassbar für andere Umgebungen
- Mehrere Zielgrößen integrierbar
- Intrinsisch adaptiv durch Lernfunktion
- Sehr reaktiv nach erfolgtem Training

- Konvergenz in lokale Optima
- Robustheit: Hyperparameter und Reward-Design
- Integration stark verschiedenartiger Ziele/Systeme
- Reproduzierbarkeit durch Stochastizität
- Nachvollziehbarkeit der Entscheidungen
- Performance bei Unit-Commitment und Zeitversatz



Modellgestützte Optimierung

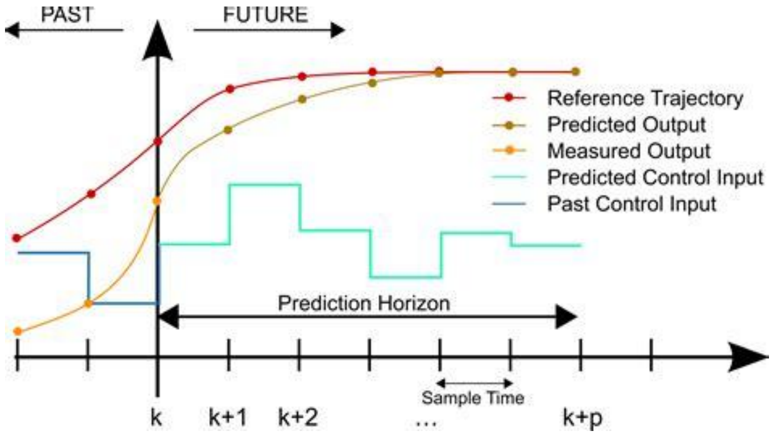
The Model Predictive Control Approach

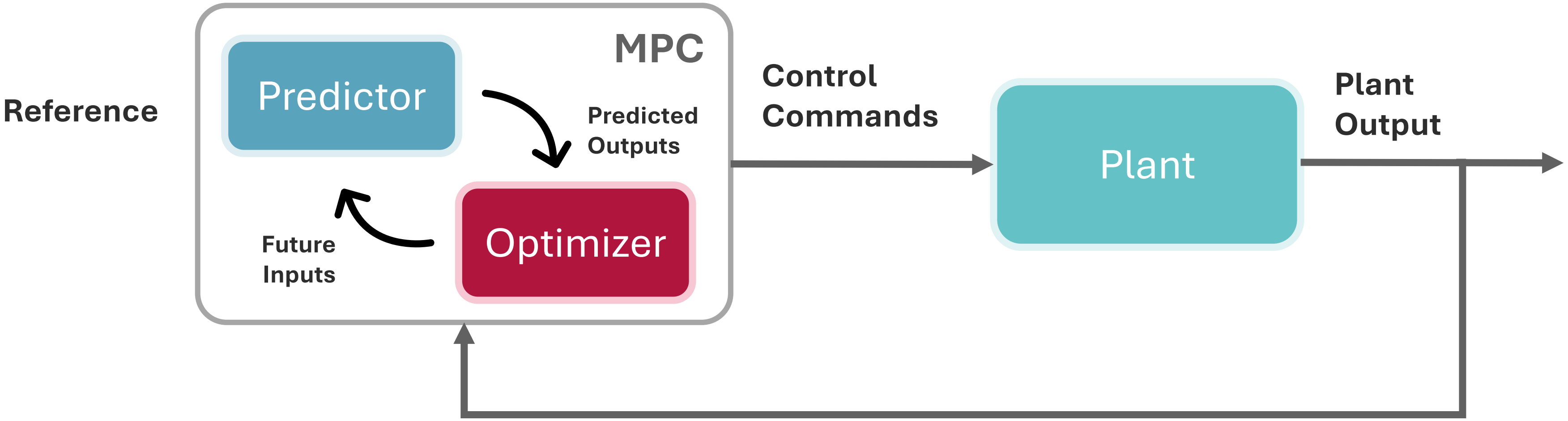
Powerful 1-shot optimization based on well-fitted plant models and mathematical optimization

Find: Control command sequences over prediction interval

Objective: Minimize cost function
(control performance requirements)

Constraints: (In)Equalities constraints
(plant response limitations)





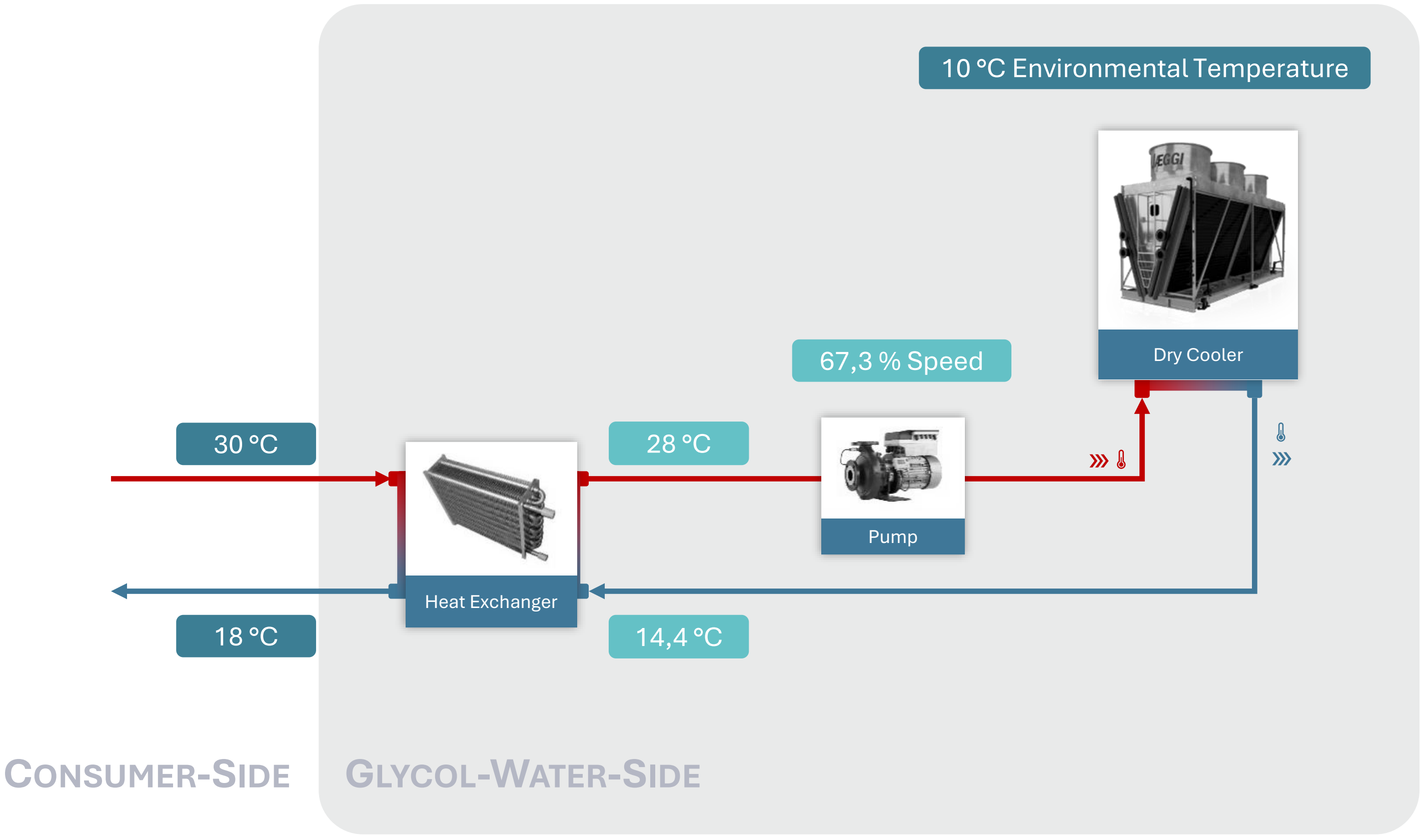
Der Begriff der Optimierung, im mathematischen Sinne verwendet, bedeutet die Bestimmung des Maximums oder Minimums einer Funktion f, die auf einem (beschränkten) Bereich S oder Zustandsraum definiert ist.

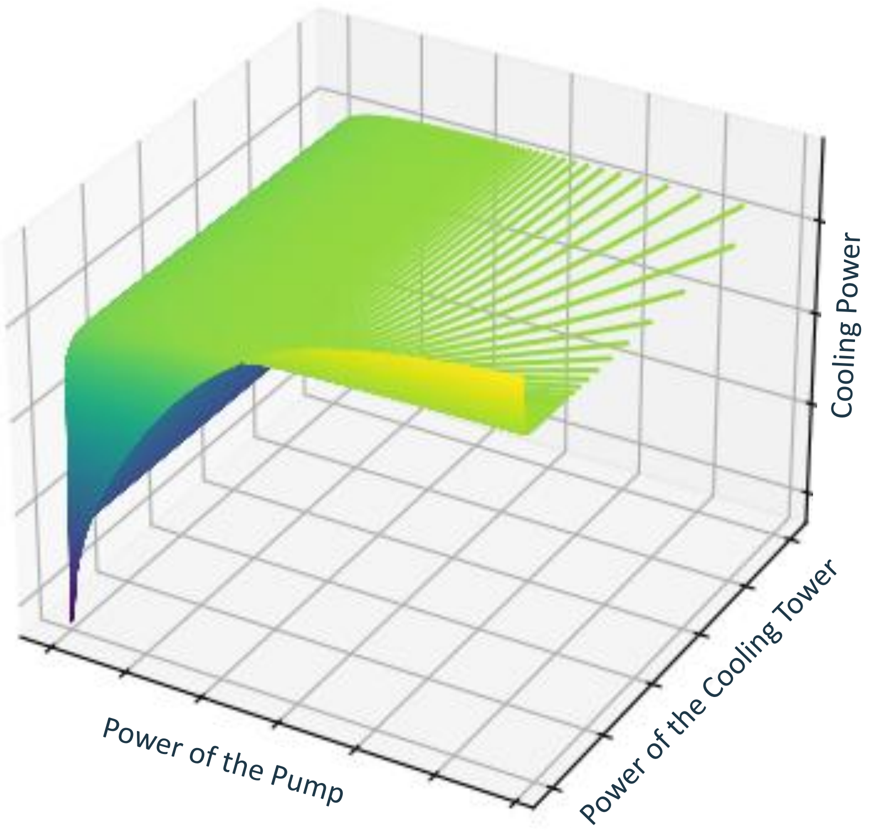
- Kallrath, 2013, Gemischt-ganzzahlige Optimierung: Modellierung in der Praxis

Example: Typical optimization measures

Simplified Scenario

Optimized Control

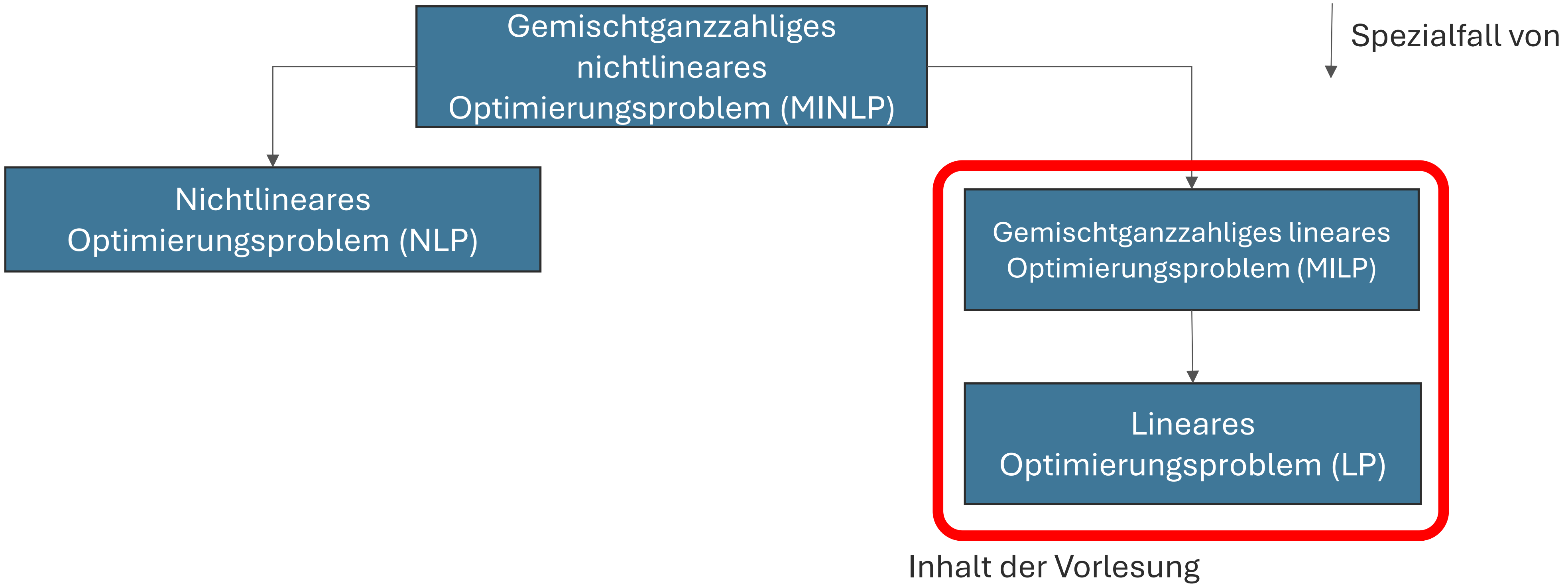




Klassifizierungen von Optimierungsproblemen

Optimierung

Nebenbedingungen	Vorhanden		nicht vorhanden
Linearität der Abhängigkeiten	linear		nicht-linear
Datentypen	ganzzahlig	nicht-ganzzahlig	gemischtganzzahlig



Überblick: Verfahren zur Lösung von Optimierungsproblemen

Optimierung

Verfahren zur Lösung von Optimierungsproblemen

- **Enumeration**
- **Metaheuristiken und heuristische Verfahren**
  - Genetischer Algorithmus
  - Ameisenkolonie-Suche
  - Simulierte Abkühlung
  - Partikelschwarm-Optimierung
  - etc.
- **Exakte Lösungsverfahren**
  - Simplex-Verfahren
  - Innerepunkte-Verfahren
  - Branch-and-Bound-Verfahren
  - etc.

Formulierung eines linearen Optimierungsproblems (LP)

Quelle: Vorlesung Energiesystemtechnik, Lehrstuhl für Technische Thermodynamik, RWTH Aachen

Elemente

- Zielfunktion $f(x) = cx = c_1x_1 + c_2x_2 + \cdots + c_nx_n$
    - Zu minimieren / maximieren
- Vektor von Entscheidungsvariablen $x = (x_1, \ldots, x_n)$
    - Veränderliche unbekannte Größen
- m unterschiedliche Nebenbedingungen

  $a_1x \leq b_1$

  $\ldots$

  $a_mx \leq b_m$

    - Bilanzen (Masse, Energie, ...)
    - Anlagenmodell / -kennlinien
    - Beschränkungen (physikalisch/technisch, mathematisch, gesetzlich)

Formulierung als Matrix

$$min\,\{cx \mid Ax \leq b, x \geq 0\}$$

$x \in \mathbb{R}^n$

$c \in \mathbb{R}^n$

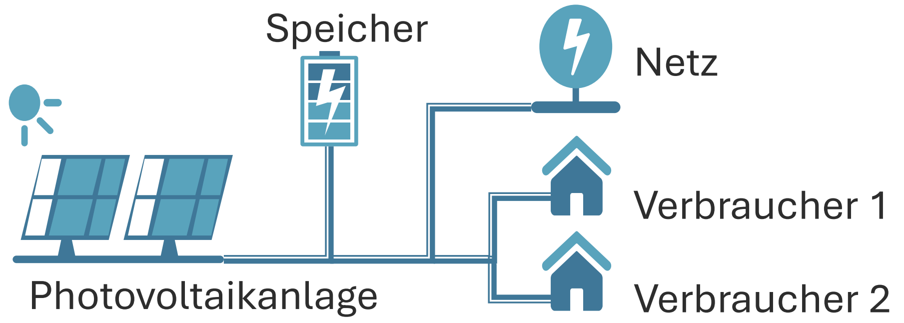
$A \in \mathbb{R}^{m,n}$

$b \in \mathbb{R}^m$

Betriebsoptimierung eines Microgrids (LP) - Mathematische Optimierung Energiesysteme

Entscheidungsvariablen: $P_{Speicher,t}$; $E_{Speicher,t}$; $P_{Netz,t}$ $\forall t$

Fallbeispiel



Parameter

- $P_{PV,t(1-4)} = [30; 4; 70; 103] kW$
- $Kap = 100\ kWh$ $E_{start} = 50\ kWh$
- $P_{max,Speicher} = 100\ kW$
- $P_{Bedarf,t(1-4)} = [50; 52; 45; 70] kW$
- $c_{Börse} = [20; 96; 40; 15] €/MWh$
- $\Delta t = 1\ h$

Mathematische Formulierung

Zielfunktion

$\min \sum_{t=1}^{4} c_{Börse} \cdot P_{Netz,t}$

Bilanzgleichung elektrische Energie

$0 = P_{Netz,t} + P_{Bedarf,t} + P_{Speicher,t} - P_{PV,t}$

Bilanzgleichung Speicher

$E_{Speicher,t+1} = P_{Speicher,t} * \Delta t + E_{Speicher,t}$

Speicherleistungsbeschränkung

$-P_{max,Speicher} \leq P_{Speicher,t} \leq P_{max,Speicher}$

Kapazitätsbeschränkung

$0 \leq E_{Speicher,t} \leq Kap$

Alle Zeitschritte

$\forall t$

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Backend

Automatic Load Testing

Predictive Platform Ops

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(Self-Service) Scenario Simulations

Next-level Data Visualization

Self-Service Optimization

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