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AI for Microgrid System Planning and Design

London – 10th Microgrid Global Innovation Forum

Using Artificial Intelligence (AI) to reduce costs and emissions in the energy sector

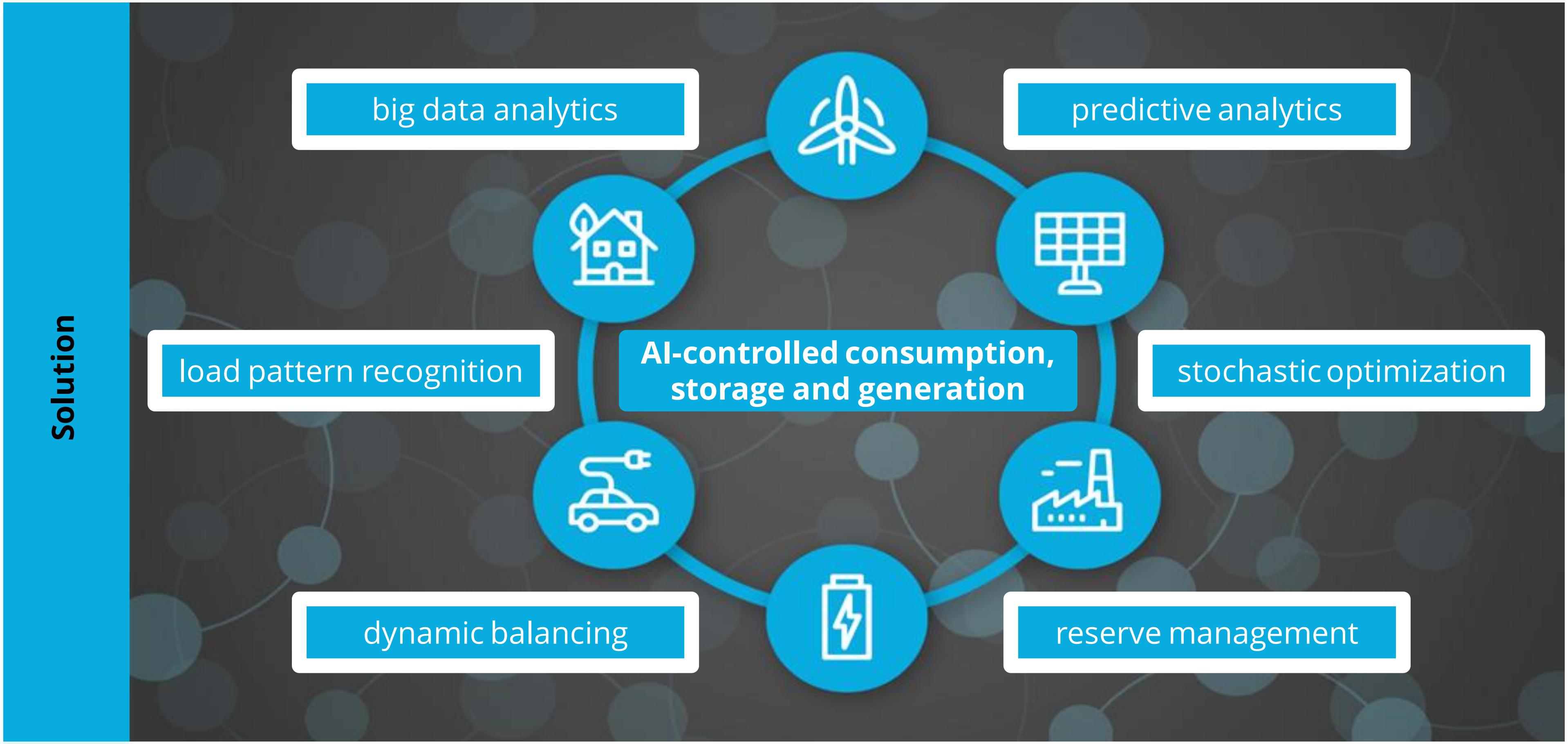
Problem

Up to 2040 about 67 trillion US-Dollar investments in the energy sector are needed to achieve current global CO_2-reduction targets

(Source: International Energy Agency)

How to make energy systems smarter and reduce these costs?

With "Q-System" we implement AI to support an efficient design and control of energy applications



AI has several advantages compared to standard optimization techniques (e.g. Linear Programming)

Advantages

- Full stochastic optimization
- Modelling non-linear behavior
- Calculation speed of trained model
- Processing large data streams
- Modelling complex dynamics

Agenda

- Introduction
- Method – Reinforcement learning based approaches
- Case Study – Benefits from using AI for system design

An agent is trained to take actions on an environment in order to maximize a cumulative reward (or to minimize costs)

Artificial Neural Network

- Observation / Data
- Valuation / Expected Reward

Agent

- Feedback / Reward
- Action / Control

Environment (Simulation of Energy System)

Agenda

- Introduction
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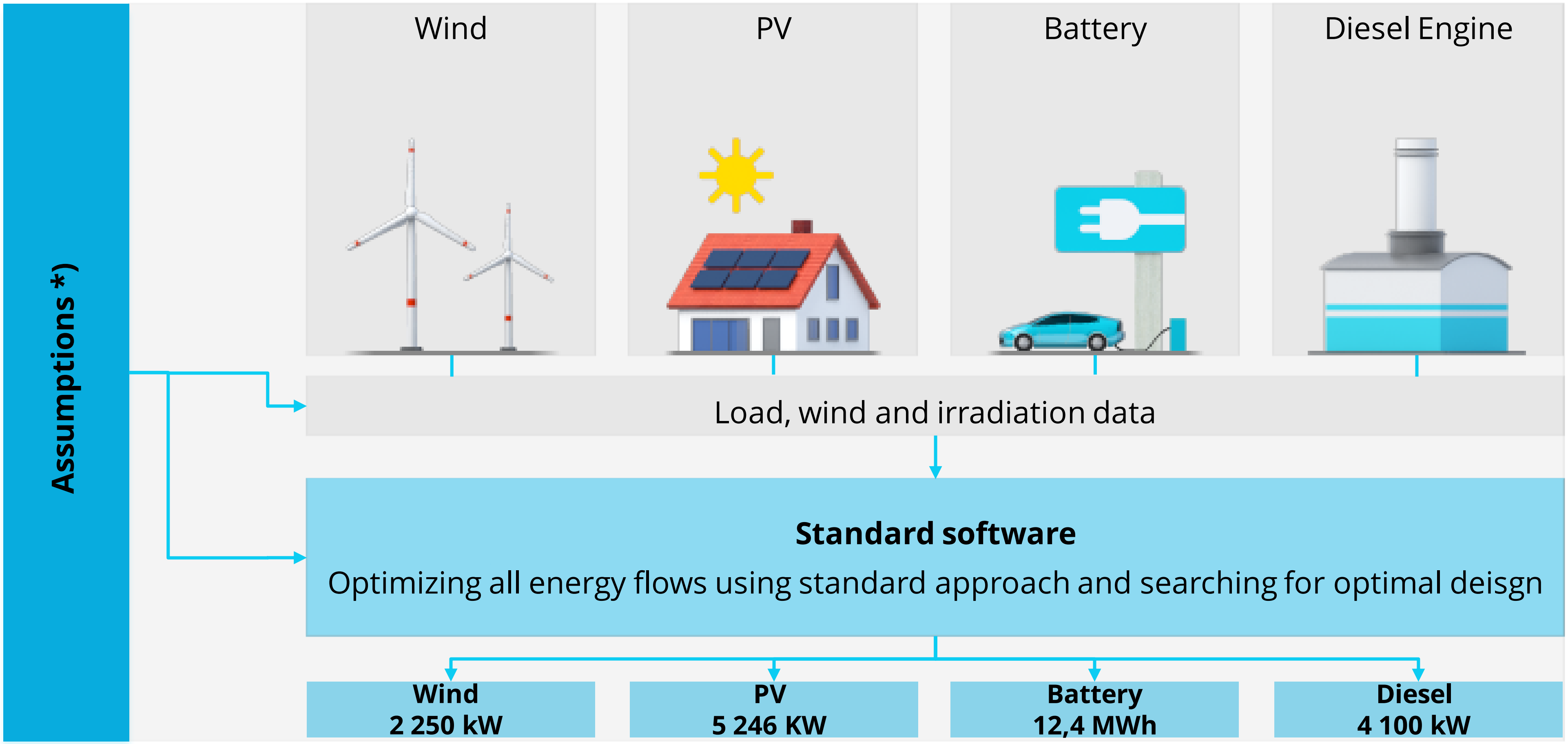
We compare our AI-based approach vs. a standard software

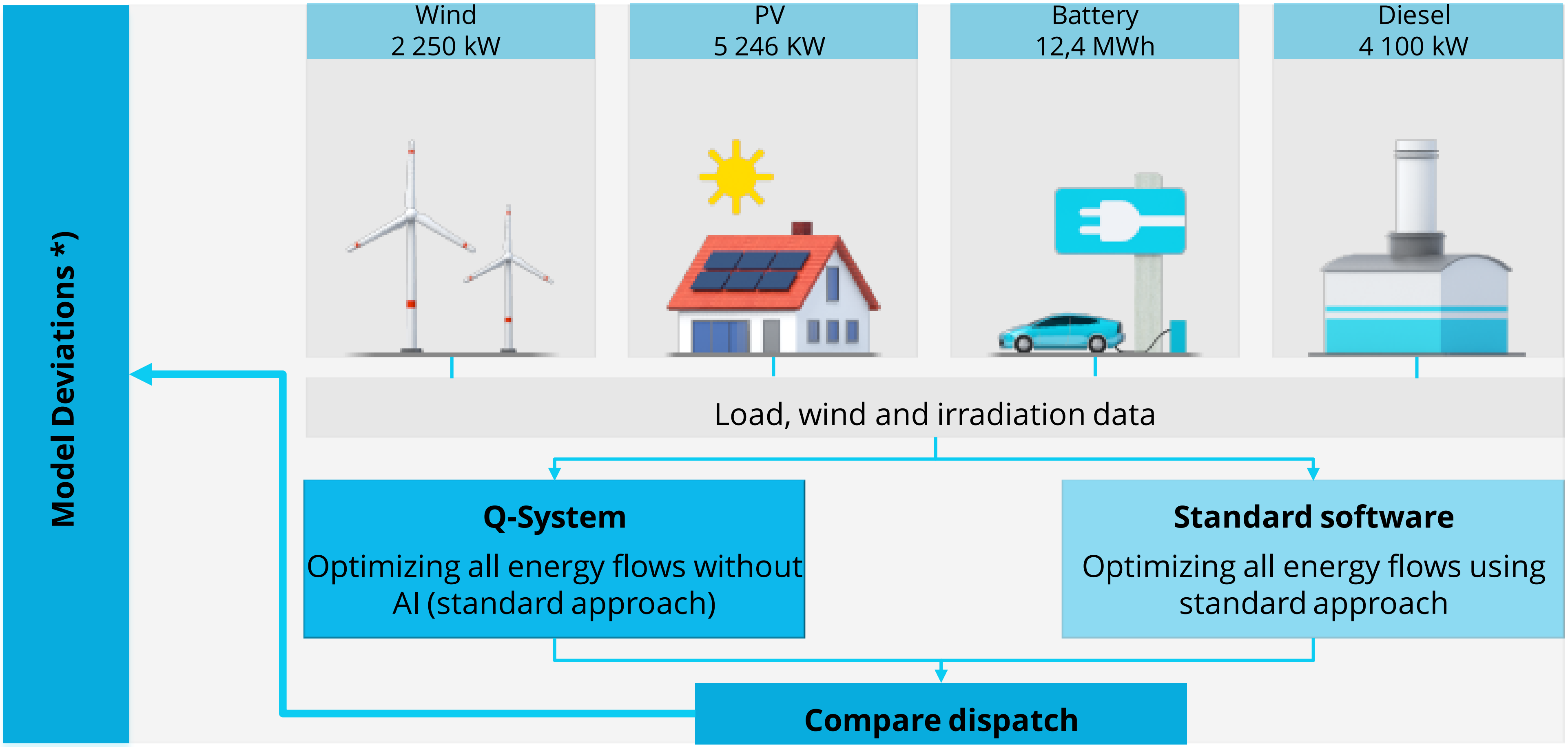
Baseline standard software	Calibrate model	Compare optimal system design
▪ Setting up a standard software for microgrid optimization and modeling to find the optimal design of a microgird ▪ Wind, PV, battery and genset have to optimally sized to serve a given load	▪ Setting up same microgrid model in Q-System (without AI) ▪ Setting same parameters for gear in Q-System ▪ Compare results and minimize deviations	▪ Using same calibrated model for all components ▪ Enabling Machine Learning in Q-System ▪ Comparing results to standard software

In this first step we set up an optimization problem with a standard software



*) Assumptions included a given hourly demand profile for the microgrid and the component behavior as modelled by the standard software

In the second step we try to fully reproduce the results and specific component behavior of the standard software



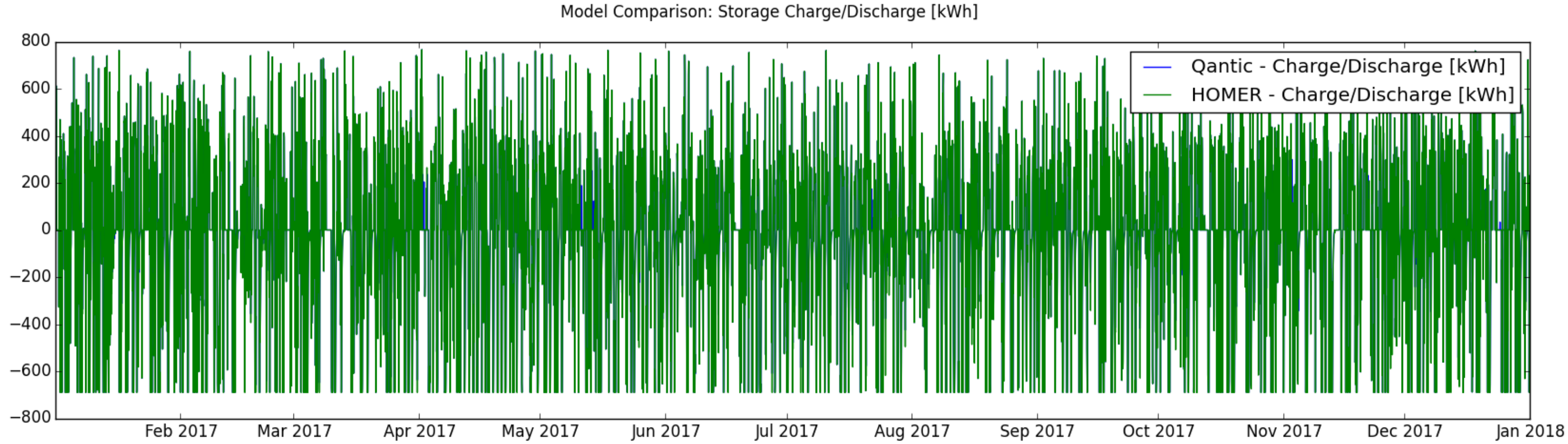
*) Deviations of the model are to be minimized in this step as we want to fully mimic component behavior and dispatch model

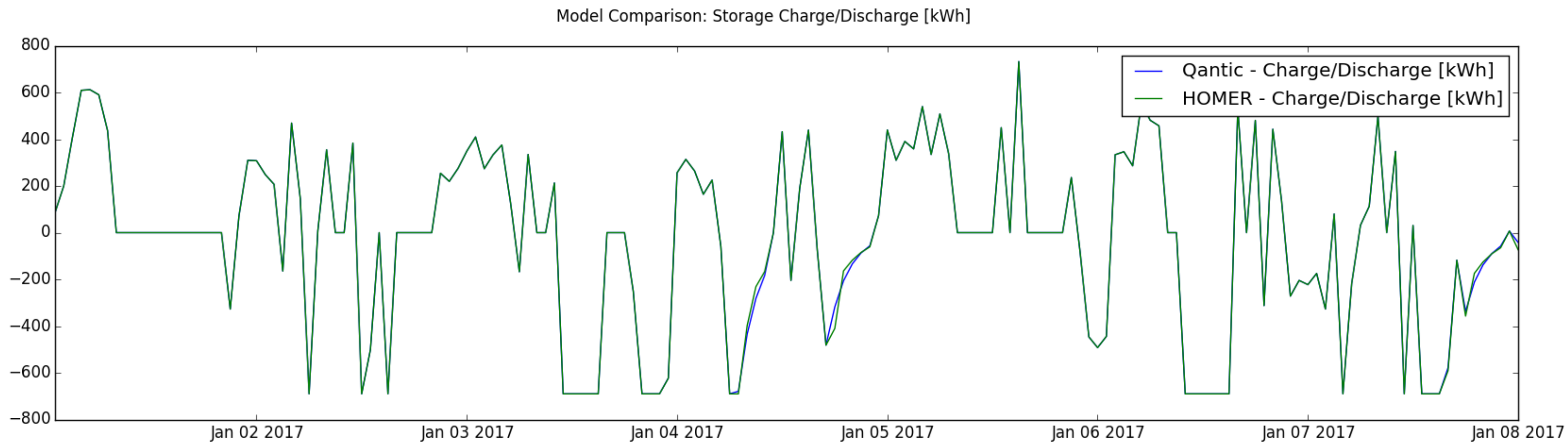
Models are fully aligned concerning component behavior to determine benefits from Machine Learning in a next step

	Q-System (with standard optimization)	Standard software
Net Present Costs	76 133 kEUR	76 118 kEUR
Generation Genset (annually)	1 884 362 kWh	1 883 420 kWh
Operation Genset (annually)	1819 hours	1822 hours
Fuel Costs (annually)	572 474 EUR	572 835 EUR
Battery Usage (annually)	1 046 636 kWh	1 041 998 kWh

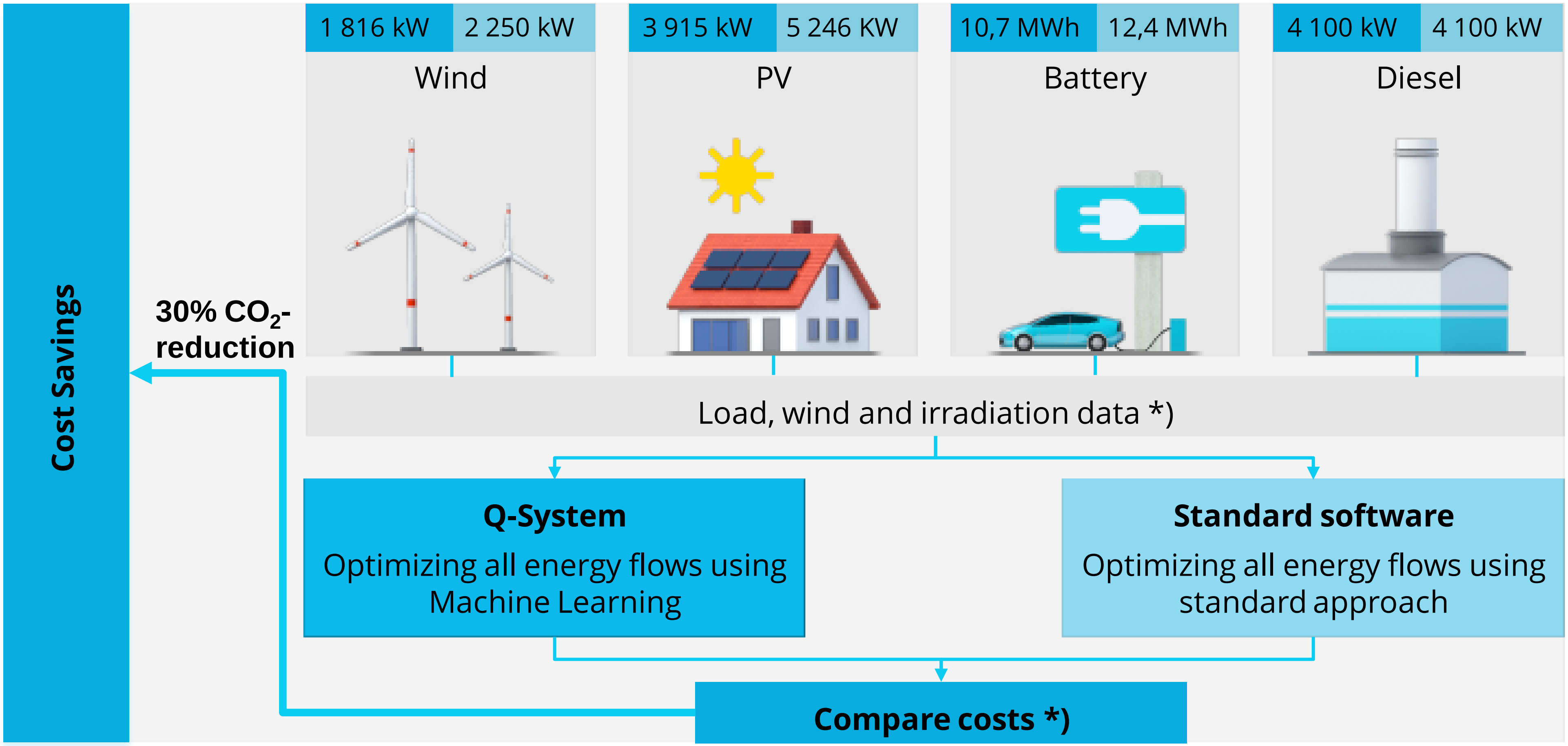
Very small deviations → Component behavior and parameters are almost fully aligned between the models

… for example the deviations in battery dispatch are extremely small and almost „invisible“





Although less renewables are installed the use of Machine Learning lowers emissions



*) To avoid any effects from over-optimization i.e. perfect foresight Q-System has been trained on different time-series, whereas the validation has been done on the same set of data for Q-System and standard software

Q-System also significantly reduces costs

	Q-System (vs. Standard software)
Net Present Costs (total)	**- 8.7 %**
Fuel Costs	**- 30 %**
Initial Investment	**- 20 %**
CO2-Emissions	**- 30 %**

Costs and emissions can be significantly reduced by using AI in system design

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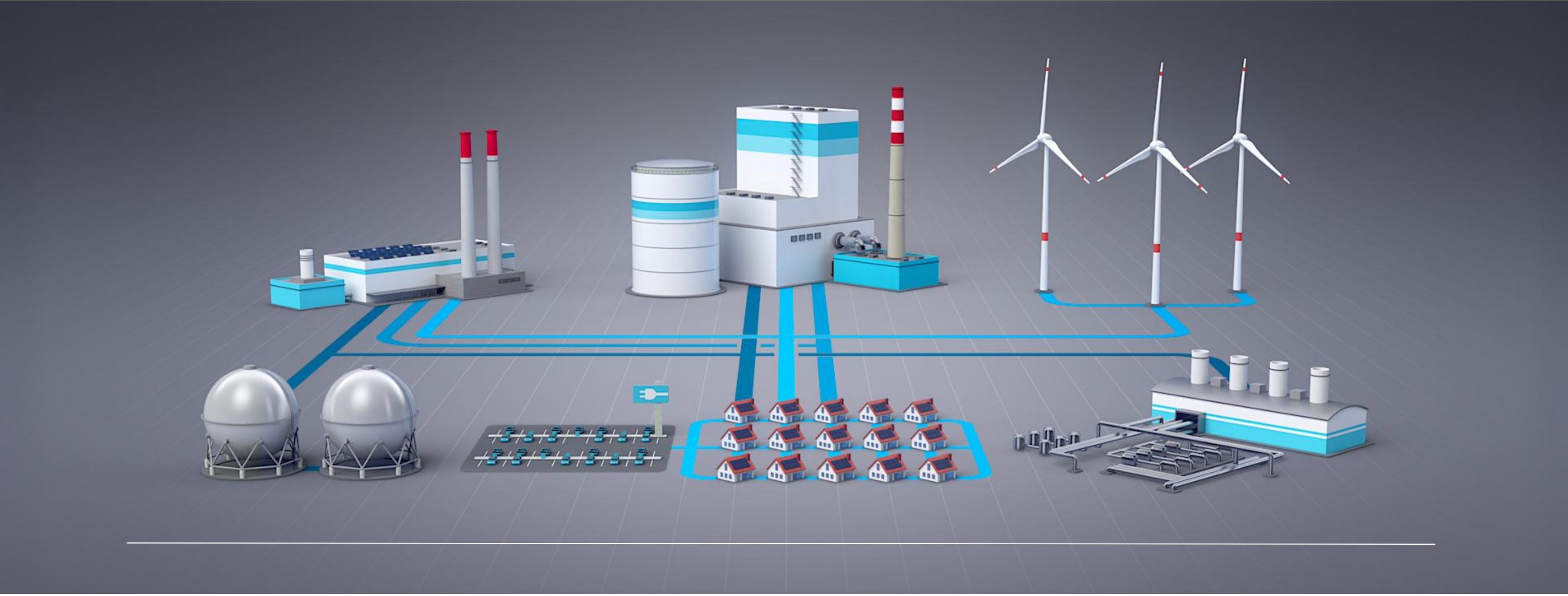
Q-System has some properties that allow it to outperform the compared standard approach

Coordination of consumption, generation and storage	Optimal dispatch to ensure efficient use of components and maximize usable RES production
Foresighted system control	Not only considering present but also future costs → e.g. avoid having to start a plant in the future or having to run it at low efficiency
Extracting value from data	Recognizing typical patterns in the data → Get better foresight e.g. on demand and production and expected future costs
Dealing with uncertainty	Preparing for different possible future developments → Also considering events with low probability but high costs (e.g. events leading to fall-out)



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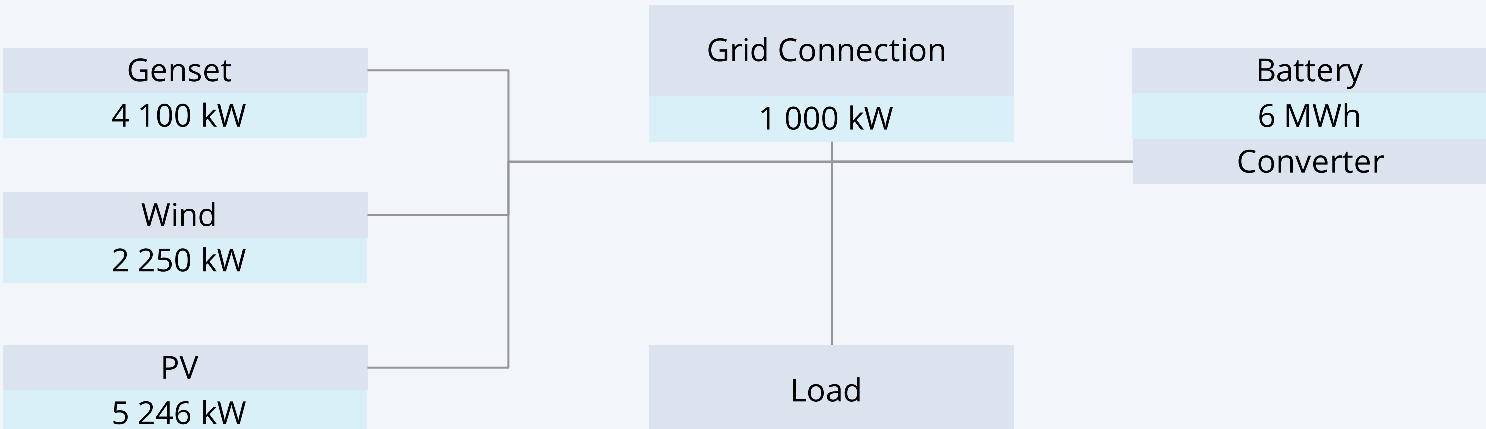
APPENDIX

Machine Learning can help to reduce costs in dispatching complex energy systems

What is our task?	Dispatching all controllable energy resources of an energy system to serve a time-varying demand at least costs
What makes it difficult?	Complex system dynamics and intertemporal effects
How would we normally solve it?	Heuristics or techniques for deterministic or stochastic optimization (e.g. dynamic programming)
What can AI do better?	Optimizing energy systems with complex system dynamics at high computation speed using large amounts of input data

AI can yield benefits if energy systems exceed a certain level of **complexity**, **computation speed** is crucial or **large amounts of input data** (e.g. measurement data, forecasts) have to be processed

The system is dispatched by ML and a heuristic and the results are compared: Costs are reduced by 16.9 % using ML



- Using input data for one representative year (load, weather, ...) the system is dispatched by a heuristic used in a standard microgrid planning software ("load following") as well as with a ML model*)
- Total costs are calculated considering fuel costs, O&M and costs for replacement of genset and battery depending on operation regime
- Costs can be reduced by **16.9 %** using DRL

*) To be able to calculate the results for a representative period (a full year) we switched to a lower resolution than 20 ms

AI allows high quality optimizations

Heuristics

Straightforward approaches to control system by following a set of easy implementable rules

→Suboptimal results

→Easy to implement

→High calculation speed

Deterministic Optimization

Full optimization of the system control, e.g. Dynamic Programming (DP) or Mixed Integer Linear Programming (MILP). Using singular forecasts

→Neglecting uncertainty (suboptimal results)

→Representation of system can be challenging

Stochastic Optimization (conventional)

Same as deterministic optimization but using scenarios to represent uncertainties, e.g. stochastic DP or MILP approaches

→Theoretically optimal

→Usually simplifications needed to keep model computationally tractable (suboptimal results)

→Low calculation speed

Reinforcement Learning based AI

Stochastic optimization using AI with a freely choosable simulation model of the system

→Lowest restrictions in the representation of the energy system (detailed modeling possible)

→Very good coverage of stochastic aspects

→High calculation speed