How to benefit from AI in designing your off-grid electricity project?

White Paper

Executive Summary

What to expect from this white paper?

Dear reader,

in this white paper we present a possibility to benefit from an AI based approach in energy system design.

We give a brief overview on how AI works (particularly deep reinforcement learning) and how to use it to determine the optimal economic dispatch of an energy system.

You will read about the methodology we follow for a comparison of AI vs. a standard software based on a case study of an off-grid microgrid project of one of our clients.

We find that the AI approach leads to a different system design and performance.

Benefits compared to the standard software are

- 20% lower initial invest
- 30% lower emissions
- 8.7% lower levelized costs of electricity

If you find this information useful in your day-to-day work, feel free to reach out for an inspiring dialogue with me or my colleagues.

Have a nice read.

Best regards,

Thomas Kalitzky | Managing Director | Qantic GmbH

CONTENT

Why do we need software tools to design microgrids?

Improving decisions

Investing in power assets is cost-intensive. Therefore, a well informed decision that involves most of the available data is crucial. Software products help to guide the process of extracting value from this data.

Estimation of performance

Considering comprehensive data, software helps us to compute information quickly for the use in day-to-day business and condense information to give a full picture of the estimated project performance.

Comparing options

Comparing results gives us an idea of different options. Software products help to better understand the systems sensitivity toward changes in the assumptions or future requirements.

Dealing with uncertainty

A look into the future is always uncertain – therefore comprehensive energy models lower risk by using a methodology rather than gut feeling and help to develop robust business models.

To simulate the system we need to choose an appropriate economic dispatch strategy: AI enables high quality optimization

Heuristics & Rule Based Methods

Rule of Thumb like Approach

Straight forward approaches to control power systems by following a set of easy implementable rules.

- Easy to implement
- High calculation speed
- But suboptimal results

Deterministic Optimization

Simplified System under Perfect Foresight

Full optimization of the power system control, e.g. Mixed-Integer Linear Programming or Dynamic Programming.

- Representation of system can be challanging
- Neglecting uncertanty

Stochastic Optimization

Simplified System under Uncertainty

Same as deterministic optimization but using scenarios to represent uncertainties, e.g. Stochastic Dynamic Programming approaches.

- Theoretically optimal
- Usually needs simplifications
- Low calculation speed

Deep Reinforcement Learning

Detailed System under Uncertainty

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

- Lowest restrictions in the representation of the power system, detailed modelling is possible
- Very good coverage of stochastic aspects
- High calculation speed (of trained model)

The accuracy of results … … is expected to increase

<u>Definition</u>: The **Economic Dispatch** is the procedure by which an operator selects which of its generators produces at what time to meet electricity demand. It also considers the charge and discharge from batteries.

= Method investigated in this study

AI can yield benefits, if power systems exceed a certain level of complexity, when computation speed is crucial or large amount of input data have to be processes (e.g. measurements or forecasts).

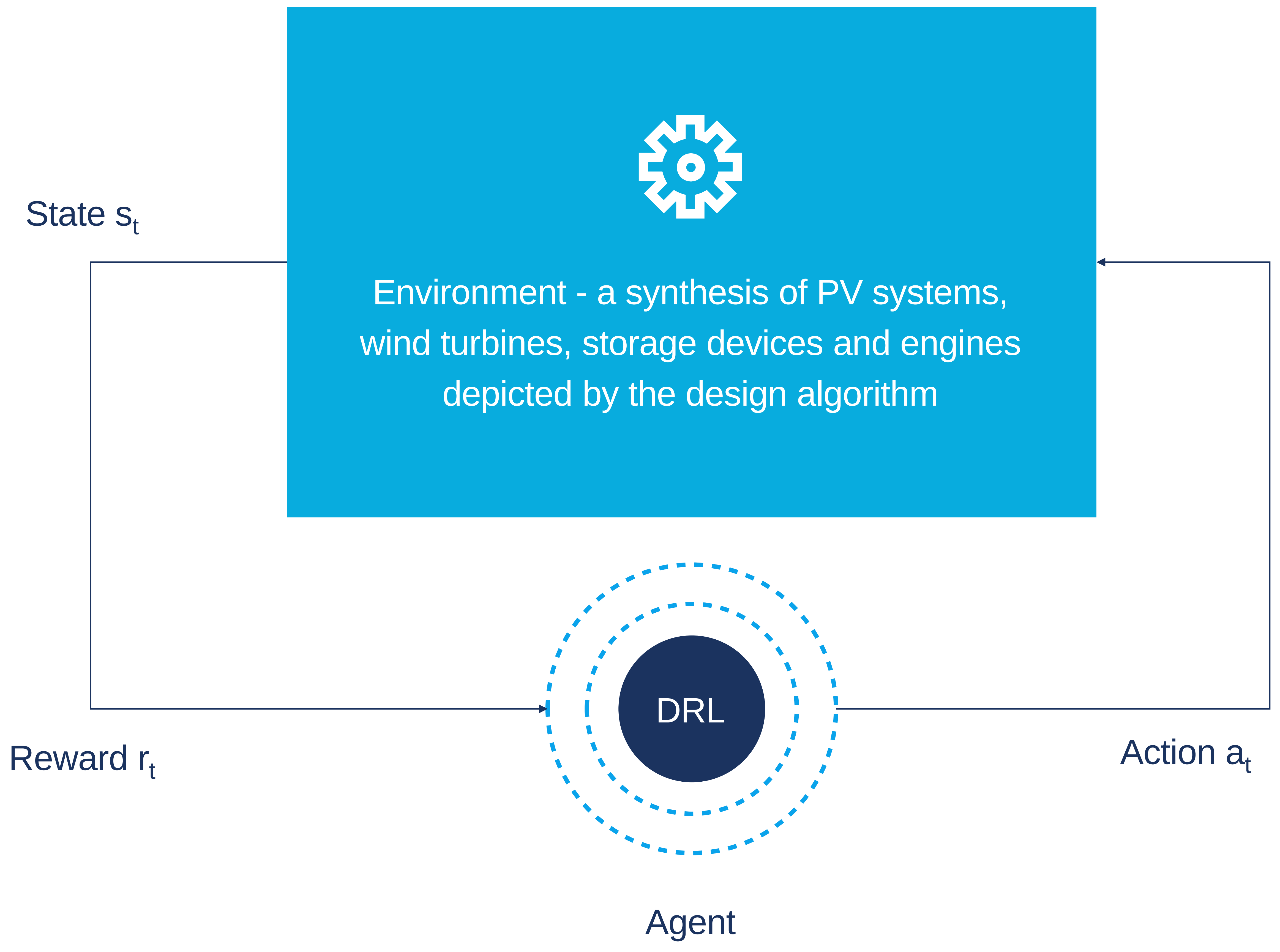
How does
Deep Reinforcement Learning work?

Applications in the field of Deep Reinforcement Learning (DRL) are a subfield of Machine Learning techniques and come under the discipline of Artificial Intelligence.

In DRL, an Artificial Neuronal Network is trained to guide through the decisions of a so-called **agent**. Then, the agent takes actions on an **environment** (e.g. power assets within a microgrids) in order to **maximise a cumulative reward** or minimze costs.

The change of **state s_t** is conceived as a sequential decision process (as Markov Decision Process). The s_t (e.g. state of charge of a storage device) can be changed by **actions a_t** that are pre-defined in advance (e.g. ramp-up gas engine). Furthermore, a metric is introduced to evaluate the quality of respective actions and the resulting states as a **reward function r_t**.

During a **training**, the algorithm learns by interacting with the environment to choose the actions that maximise the reward respectively. The trained model can then be used for the simulation or operation of the system.



Comparison of system design: We compare Deep Reinforcement Learning to the heuristic from a standard software

Baseline standard software	→	Calibration of technical parameters	→	Determine optimal dispatch and design with DRL	→	Compare results and evaluate benefits of DRL
Setting up a standard software for **microgrid optimization** and modelling to determine the **optimal sizing of components** in a microgrid project. PV systems, wind turbines, storage devices and engines will be sized to serve a given load, optimally at lowest **Levelized Costs of Electrictiy (LCOE)**.		Calibrating the DRL model to use **the same parameters** for the gear and compare its results and minimize deviations in the technical assumptions of the used gear. Goal of this step is to **avoid any bias** from using different parameters or assumptions in **technical characteristics** of the component.		Perform a **system optimization** using the **DRL** algorithm (system design with **lowest LCOE**). Using **same calibrated model** and requirements for all microgrid components as in the standard software. Only difference to standard software is the **optimization technique** itself.		Comparing overall design and system performance with standard software. Comparing all energy flows, **net present costs, fuel costs, initial investment and CO_2 emissions** to evaluate the **benefits** of using **DRL** as compared to the baseline

Case study: off-grid design in Indo-Pacific rural areas

As a case study for our comparison we want to design power assets on Indonesian island Taliabu to maximize renewable energy integration into its grid infrastructure.

Project description

For an international tender among EPC and turnkey project developers the optimal Levelized Cost Of Electricity (LOCE) has to be determined to bid a benchmark for the client

To meet the local off-grid electricity demand of the site, an economic dispatch is being calculated to design the right size of the power assets within the microgrid - the project lifecycle spans over 25 years of operation.

System design

The system design should involve **solar PV power** as well as **wind turbines**. In addition, a lithium **battery storage system** is planned to be installed to increase the electricity supply based on renewables. The existing diesel **generator** is about **4.1 MW** and can always serve the system's peak demand.

We use both solutions to determine the optimal system design in order to compare the results

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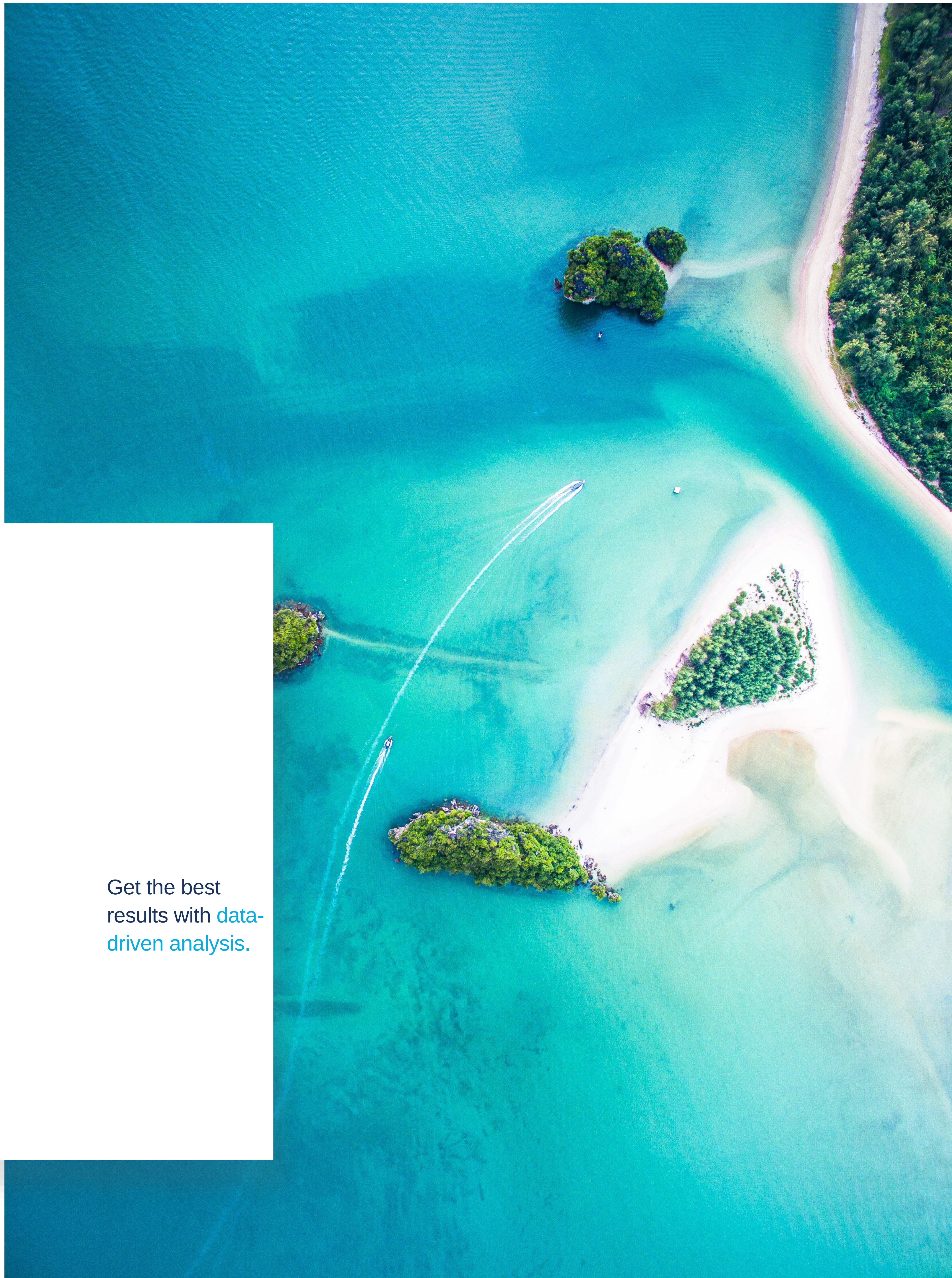


Get the best results with data-driven analysis.

With the aforementioned methodology a comparison between an economic dispatch using DRL and a heuristic is introduced - the same optimization problem is solved via both a rule based method (heuristic) from a standard software and our Deep Reinforcement Learning technique. The DRL based design algorithm leads to a different system design with lower total costs and emissions

- 8.7%

Reduction in Levelized Cost Of Electricity (LOCE).

- 20%

Reduction in initial investment.

- 30%

Reduction in CO_2 emissions.

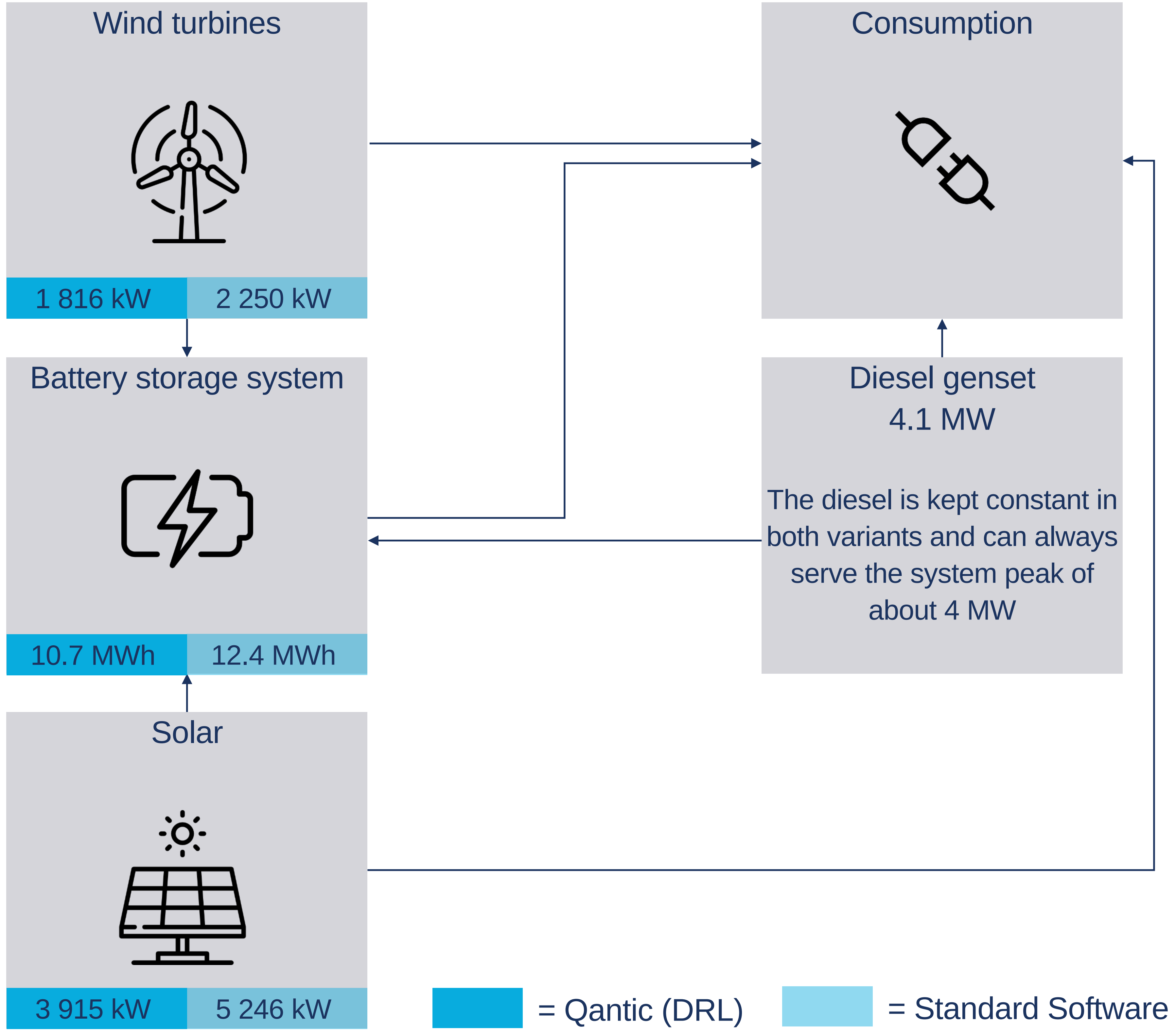
In the first step, the optimization problem is set up initially with a standard software using a heuristic. Consumption, wind speed and solar profiles in hourly resolution as well as the overall component behaviour (e.g. technical characteristics of genset and battery) is given as input. .

Then, we calibrate the component models in the DRL to fully reproduce the specific component behaviour that is assumed in the standard software. The overall component behaviour and parameters can be almost fully aligned between both approaches. Thus, we can be sure that our comparison is not biased by any significant differences in the technical assumptions of system behaviour.

However, after “switching on” the DRL optimization we get a significantly different recommendation on the optimal system design with overall lower initial investment (-20%). But also the economic dispatch of the gear seems to be optimized by the DRL as we have a higher use of renewable energy (avoid periods of curtailment) and run the genset in better points of operation (higher efficiency). These aspects lead to overall reduced fuel consumption and emissions (-30%) which, in combination with the reduced investment, reduce LCOE around 8.7% in comparison with standard software.

To avoid any effects from over-optimization i.e. perfect foresight, the DRL design algorithm has been trained on different time-series, whereas the validation has been done on the same data set in both approaches.

Comparison of System Design



AI based design vs. Standard Software

The illustration shows the differences in the design that is proposed by the standard software vs. our proposal. The demand, which is represented by a hourly load curve and the existing genset capacity is kept fixed. For the remaining components the design that minimizes LCOE is calculated in parallel by the two software solutions and compared to each other.

Lower Investment

The overall lower installed capacity of wind, PV and battery storage leads to a reduction in intial investments (-20%) that accounts for parts of the reduced LCOE compared to the standard software. But how can we reduce RES and storage capacities and also achieve lower overall emissions (-30%)?

Optimal dispatch makes better use of ressources

This is because DRL can make better use of the assets and allows for a larger amount of RES consumed which in turn reduces fuel consumption and emissions. Also the efficiency is increased by operating the genset in an optimized manner.

Interaction of battery and genset

Storing some of the genset's production by running it at higher load (and higher efficiency) in order to completely switch if off when the battery is sufficiently loaded can reduce emissions.

Dealing with RES fluctuations

However, we want to still reserve enough battery capacity to charge zero-emission RES excess. But the timing of excess is subject to uncertainty due to the fluctuating nature of renewables.

Foresighted system control under uncertainty

A main benefit of DRL in our use case is that it optimally balances the charging of RES and genset.

Where do the benefits come from?

- Foresighted battery dispatch leads to higher usable amount of RES and less curtailment of RES. Thus, less RES are installed and a high amount of it is consumed.
- More battery cycles and cumulative charge and discharge (while still taking into account increased wear) leads to less storage that must be initially installed.
- In addition to the benefits from lower initial investment, the existing genset can be run at higher efficiency and at lower operating hours. This further decreases emissions.

AI reduces CAPEX & OPEX in microgrid projects

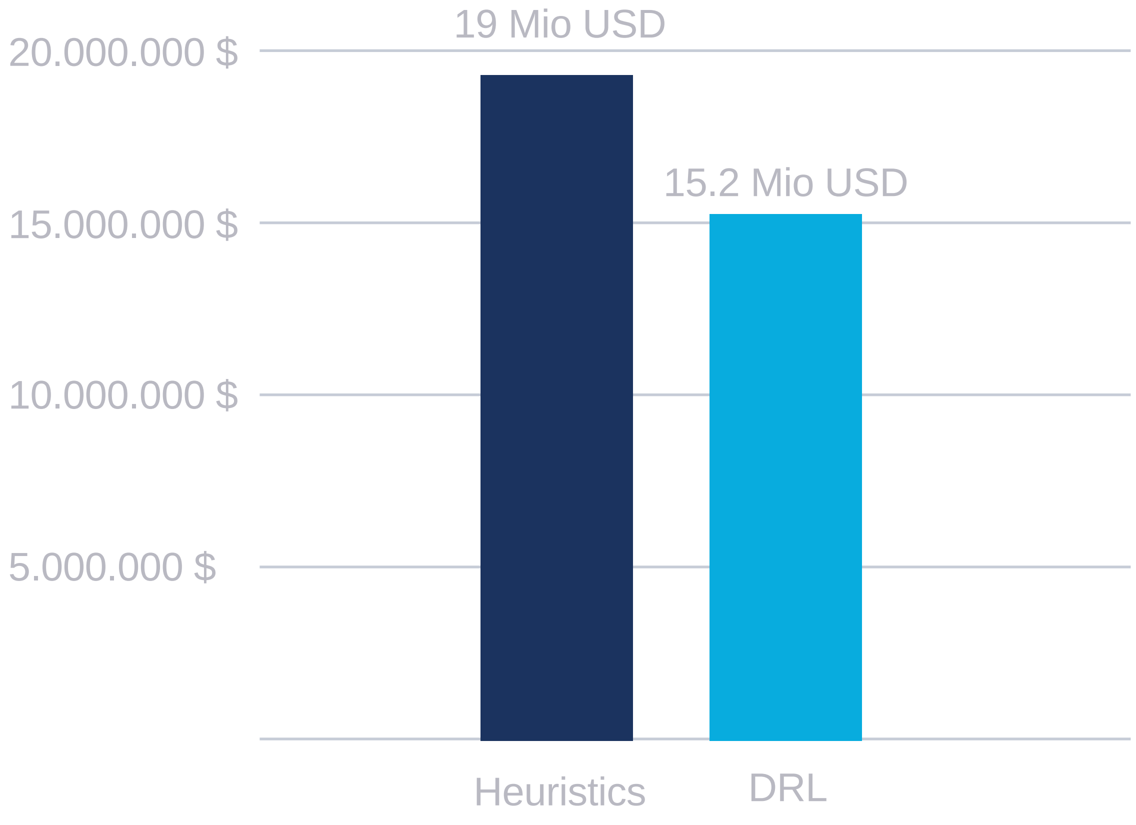
Major cost savings achieved

As a result, the Economic Dispatch based on Deep Reinforcement Learning reduces the total LCOE by 8.7% compared to conventional, numerical models used in standard software.

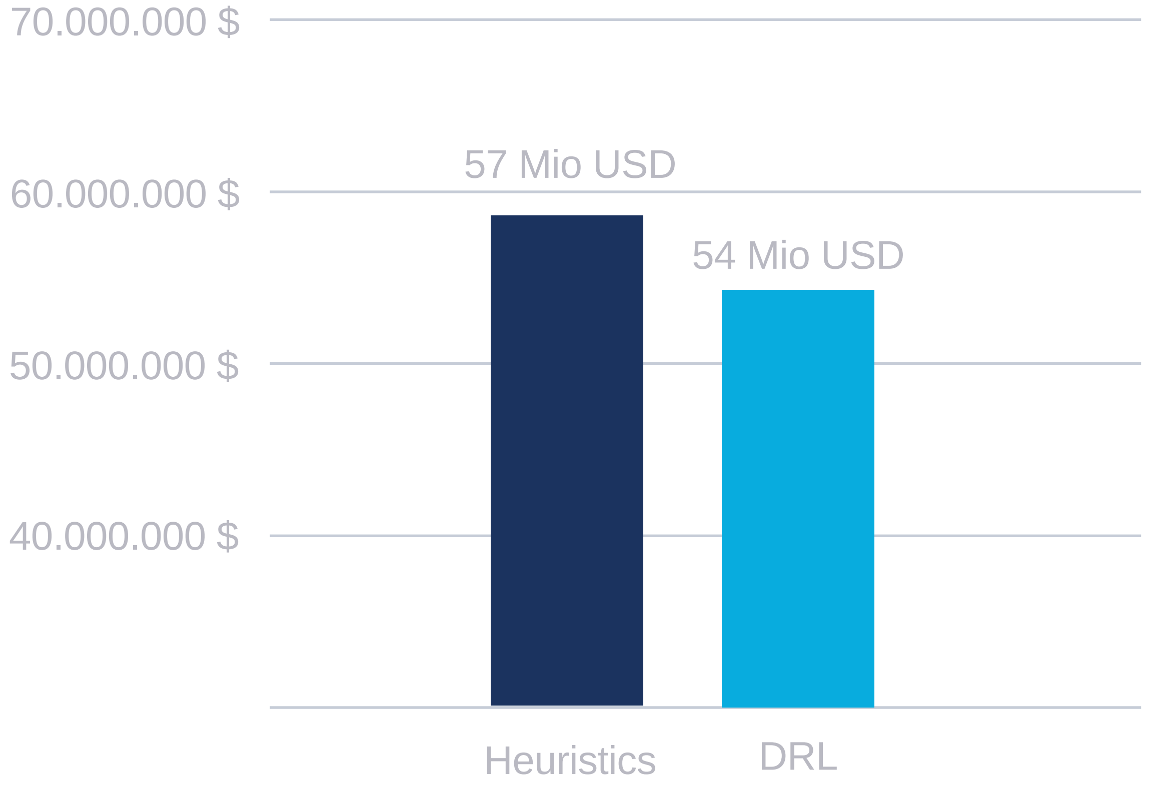
It therefore lowers initial investment about -20% and fuel costs about -30% respectively.

This comparison shows, that CAPEX and OPEX can be significantly reduced by using Deep Reinforcement Learning to match an optimal system design and its operational dispatch.

CAPEX – initial investment



OPEX and replacement
– cummulated operation of lifetime



AI lowers overall CO_2 emissions by increasing RES usage and generator efficiency

- 30%

CO_2 emissions compared with todays standard software

CO_2 emissions can be significantly reduced by using AI in system design

Periods of high renewable production that would lead to an excess and curtailment of RES are anticipated by reserving the right amount of capacity to charge the storage with this potential RES excess.

- 12 %

Of annual generator running hours compared with standard software

Genset operating hours decrease while efficiency increases

In periods were a usage of the generator is unavoidable it can be run at higher load (higher efficiency) while charging the battery. However, we must still reserve enough capacity for future RES charging as well. DRL optimally balances these conflicting aspects.

Providing accuracy in arbitrage trading and revenue stacking

Percent of theoretical maximum

> 95 %

Real-time optimization possible with pretrained models

Computation speed

~ 20 ms

Tenders successful in around 20 minutes, reduce workload

Workload

~ 20 min

Project managers can work simultaniously on tenders

Productivity increased

10+ Users

AI outperforms numerical models used in standard software

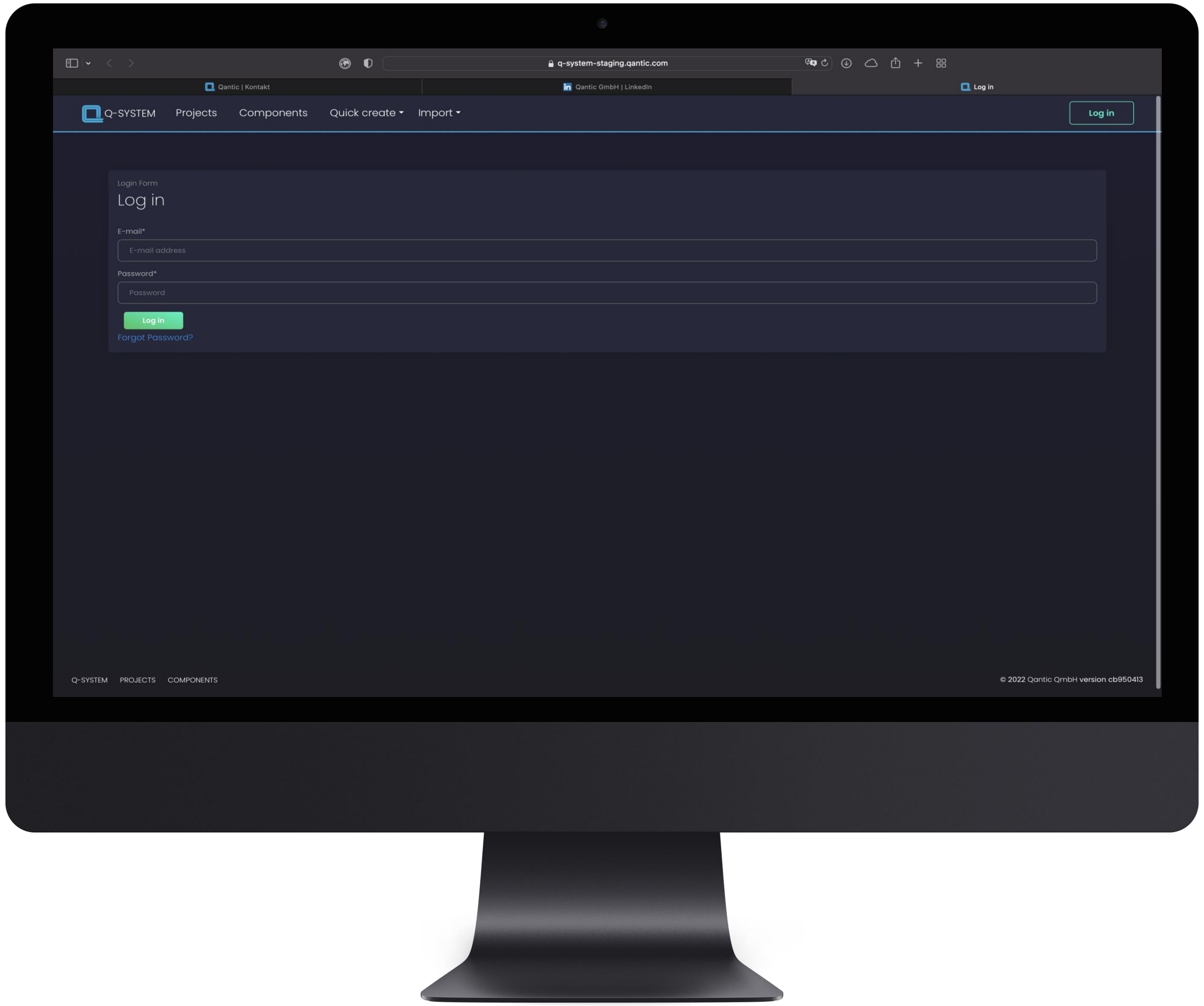
… and there are even more benefits of our AI-based applications

In our Live Demo we share an introduction of basic funtionalities of our Q-System SaaS application. Based on your interest we showcase applications for on-grid and off-grid applications.

Q-System: Microgrid Design Software

A comprehensive SaaS application to design your microgrid project – feel free to reach out to us and improve your project with artificial intelligence.

Click here & schedule a Live Demo.



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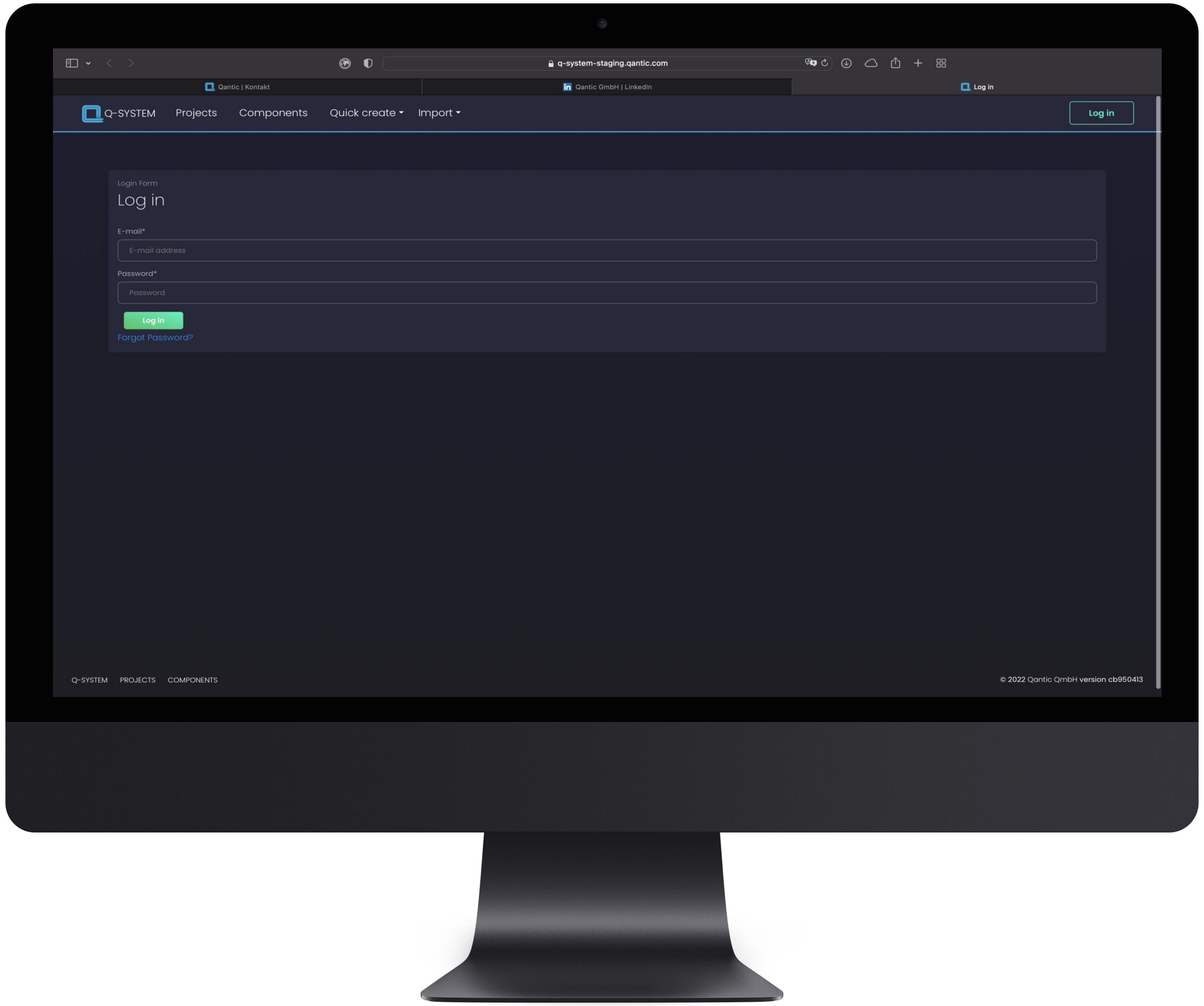

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Qantic GmbH

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QANTIC

Follow us on LinkedIn

Address:

Qantic GmbH
Lohmühlenstr. 65
12435 Berlin - GERMANY

Phone:

+49 30 89209903

Online:

support@qantic.com
www.qantic.com