Intelligent Charging Station

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Energy & **transport sector** responsible for > **50%** of global **CO2 emissions**

Achieving the **2 degree target** only with **disruptive solutions** in both sectors

> **680 thousand e-cars** in **GER** (5x more than 2020)

Changed **requirement profile**

Larger battery capacities

What if **49 million registered e-cars** in GER?

Green transport, but **dirty energy supply**?

Continued **guarantee** of **energy** in **other areas** as well

Charge Management & Network Infrastructure

The **BMVI**'s Scientific Advisory Board identified the following challenges:

Charging during **peak hours**

Expansion of the network infrastructure

Ensure **free mobility**

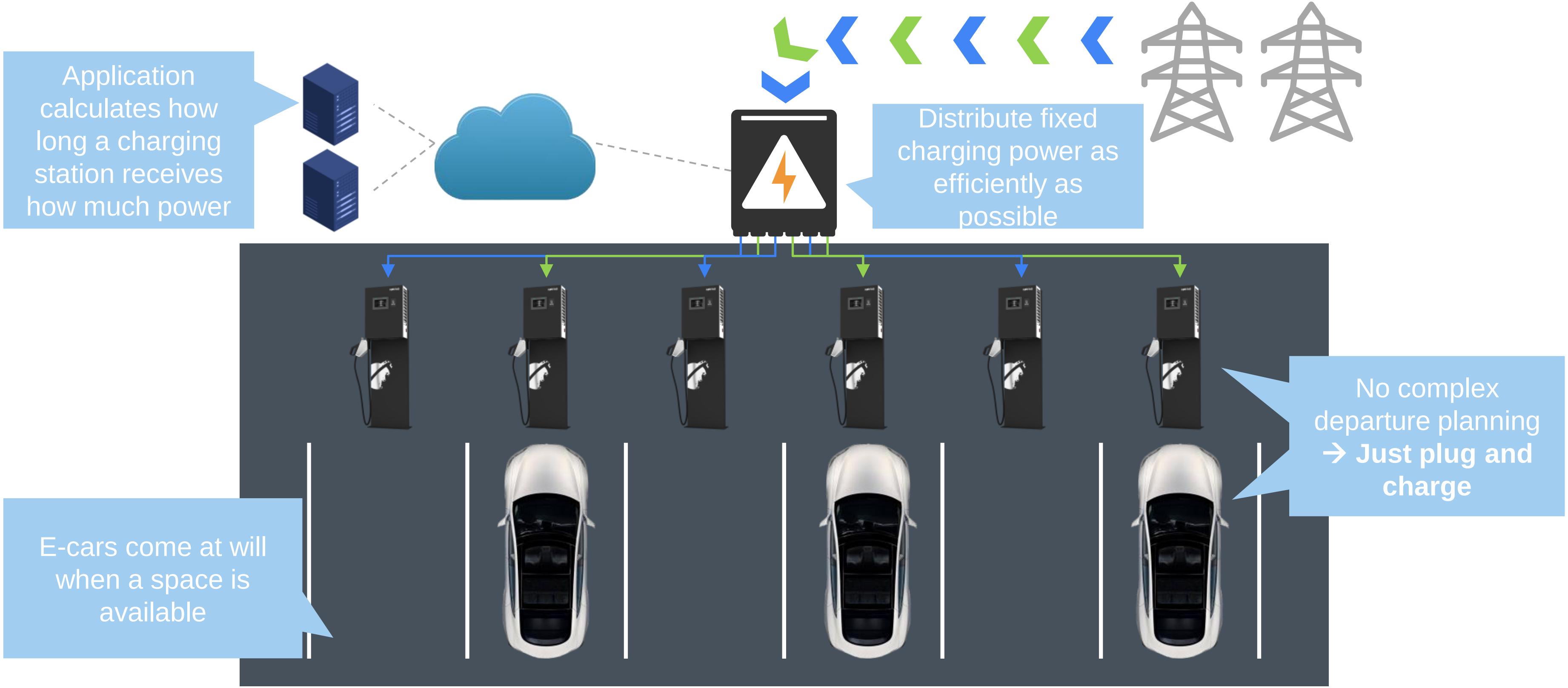
Increased demand may be difficult to meet with renewable energy sources

Examine **need** and organizational models for **charging infrastructure**

Grid stability: ensuring energy supply in other areas as well

Consider **network limitations**

Intelligent Charging Station



Reinforcement Learning

How is the state of the environment built?

What is the reward?

Which model can be used?

How is the model trained?

Position n

Position 2

Position 1

There is a vehicle on the position (True/False)

Current battery level [kWh]

Maximum battery capacity [kWh]

Number of time intervals that a vehicle has already stayed at the position

Minimum & maximum charging power [kW]

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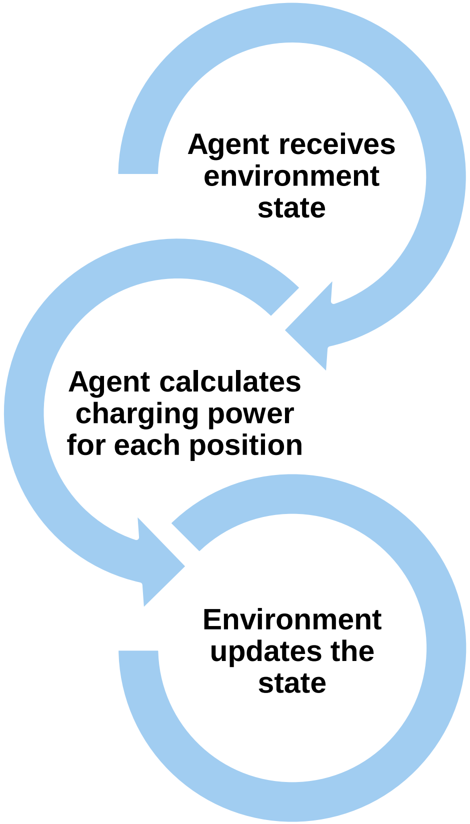
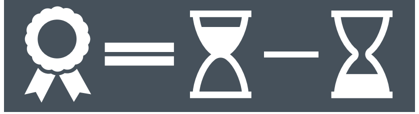


Reward corresponds to the **difference** of all **battery capacities** between the time intervals



Reinforcement Learning

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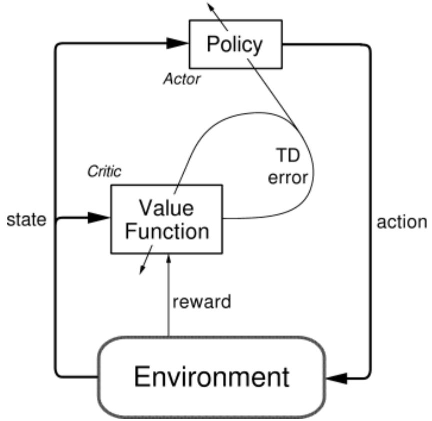
Classical DQNs are not able to make continuous predictions ...

Deep Deterministic Policy Gradient



Actor	Critic
Decides which action is to be performed	Evaluates the action of the actor and specifies how this action should be adjusted

Reinforcement Learning

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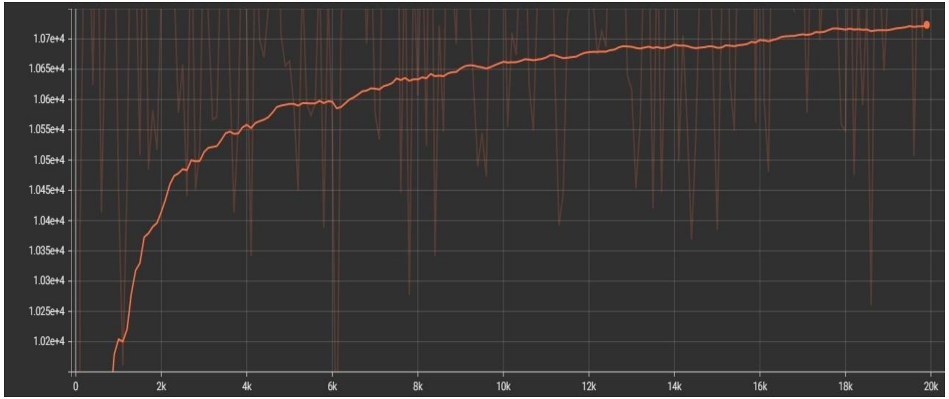
How is the model trained?

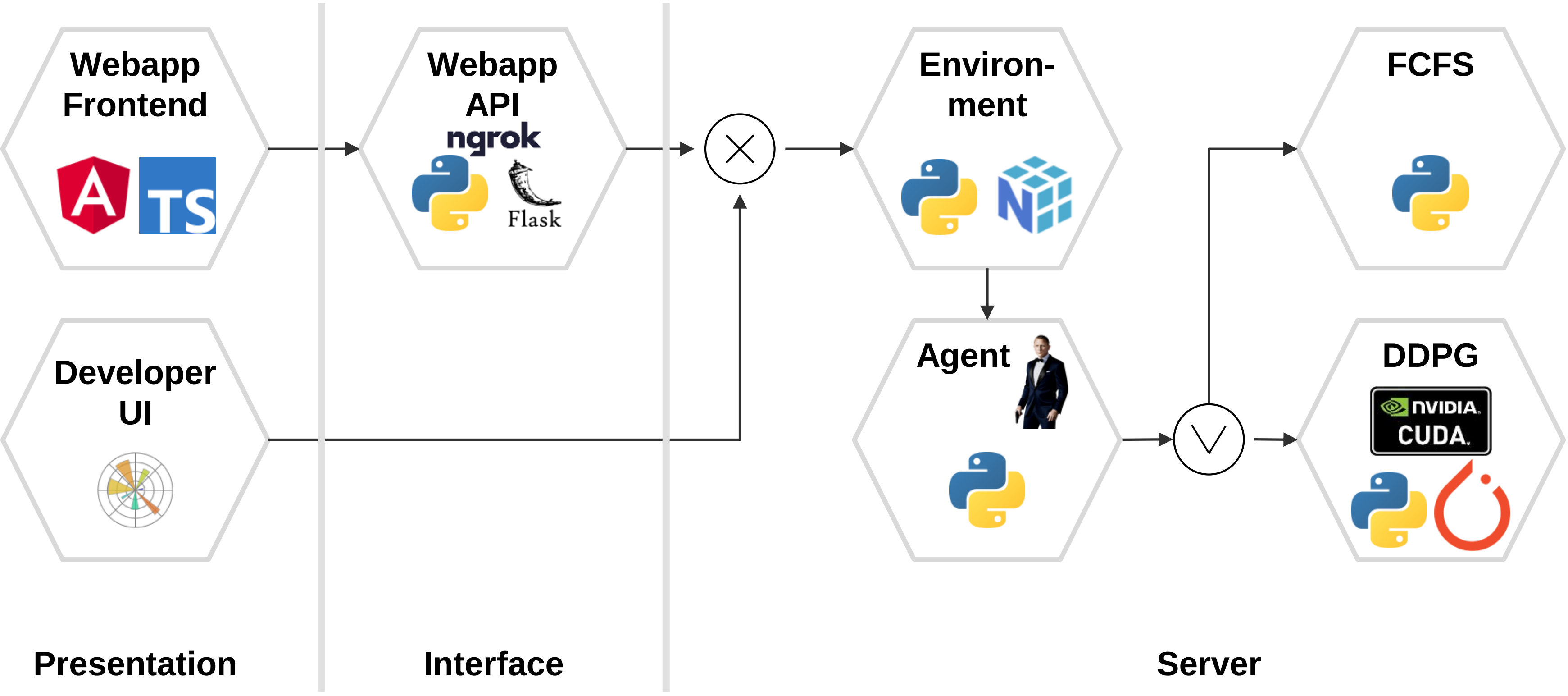
Using the **Epsilon-Greedy method**, a basic set of experience is initially accumulated during training, until gradually the agent makes more and more frequent decisions...

Decisions are temporarily stored in the **replay buffer** (queue)

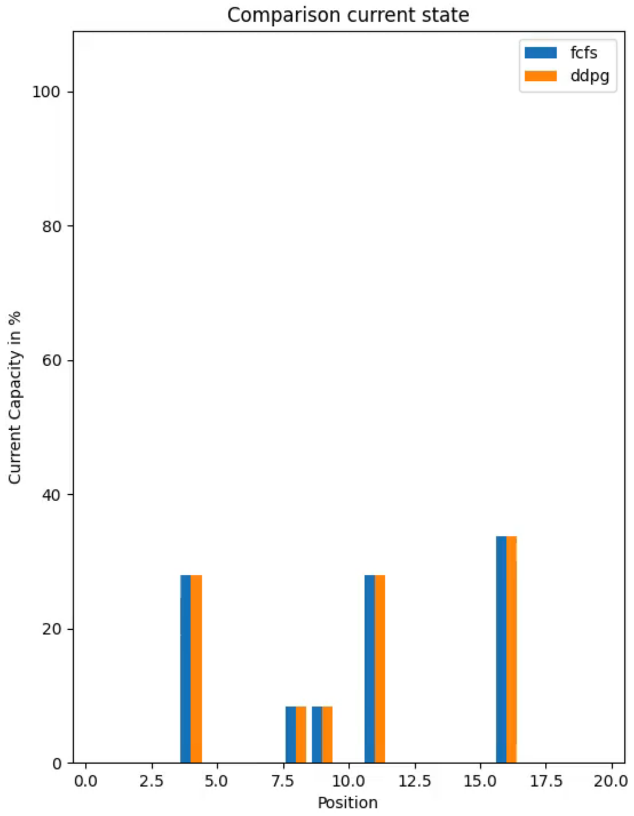
More stable learning through **target and train models**



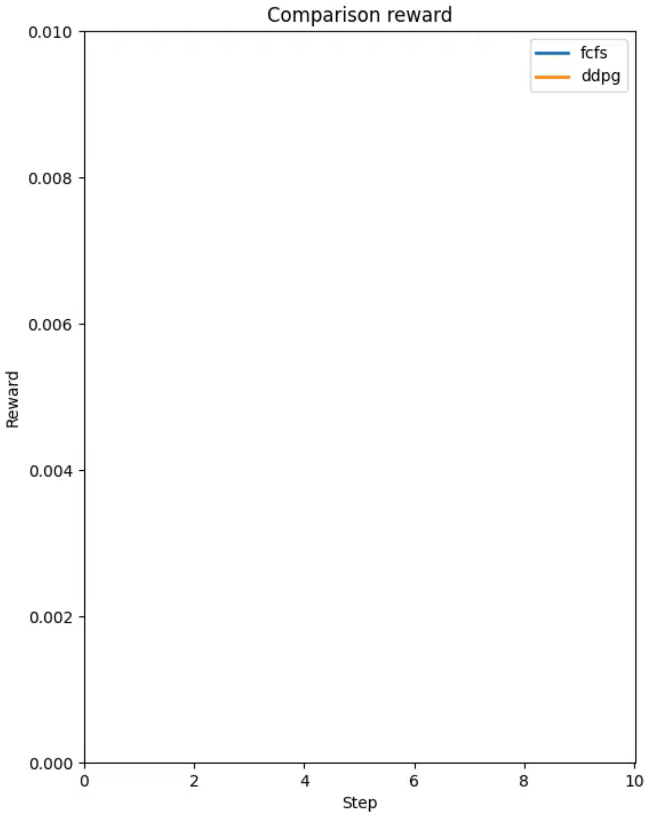
Architecture & Technology Stack



Results



Comparison current state
fcfs
ddpg
Current Capacity in %
0
20
40
60
80
100
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Position



Comparison reward
fcfs
ddpg
Reward
0.000
0.002
0.004
0.006
0.008
0.010
0
2
4
6
8
10
Step

Conclusion

Achievement of Objectives

Working AI system

Usable frontend

A "functioning" PoC can be presented to potential investors

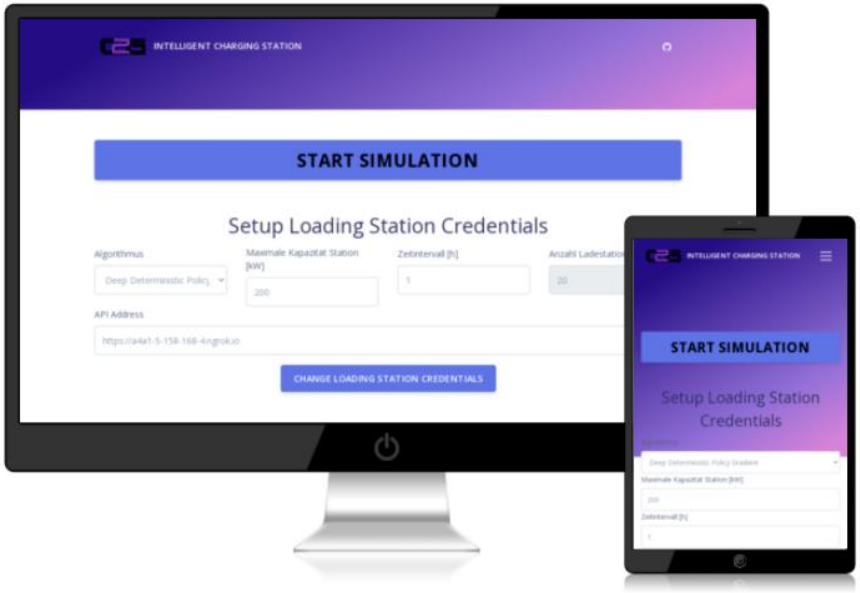
Critical Assessment

FCFS is not the most intelligent non-AI algorithm

Certain bias due to low diversity of variants during training

Battery research still in early stages → disruptive techniques may render our platform unusable

Demo


INTELLIGENT CHARGING STATION
START SIMULATION
Setup Loading Station Credentials
Algorithmus
Maximale Kapazität Station [kW]
Zeitintervall [h]
API Address
CHANGE LOADING STATION CREDENTIALS

Titel	Approach	Difference to our use case
Intelligent Electric Vehicle Charging Recommendation Based on Multi-Agent Reinforcement Learning (Link)	• each charging station corresponds to its own RL agent • Consideration of other influences such as charging competition or delayed access strategies. • Results from a conducted experiment are promising	• The paper is primarily about the generation of recommendations regarding a suitable charging station, which is based on a pool of geographically distributed charging stations.
Optimal Placement of Public Electric Vehicle Charging Stations Using Deep Reinforcement Learning (Link)	• Using projected charging demand and current charging stations to find an optimal location for new charging stations. • Factors: traffic density in the surrounding area, the registration of e-vehicles & proximity to certain types of public buildings.	• It is primarily about finding new charging stations
Smart charging of electric vehicles using reinforcement learning (Link)	• The problem to be addressed is to ensure grid stability, taking into account the charging behavior and the overall cost minimization, which is composed of supply and demand • An RL agent is designed to learn the consumption behavior of households, which takes into account the goal of individual welfare maximization • Results of the experiment are promising and based on statistical customer models • The agent was able to reduce energy prices and at the same time reduce the general load including peak loads in the grid	• In our use case, the focus is not exclusively on reducing energy prices, but on the intelligent distribution of resources

Titel	**Approach**	**Difference to our use case**
Deep reinforcement learning for energy management in a microgrid with flexible demand (Link)	• Optimized resource allocation within a novel microgrid model consisting of wind turbines, energy storage systems, a set of thermostatically controlled consumers, a set of price-dependent consumers, and a connection to the main grid • Several DL approaches were tested within one experiment • The best results were achieved by an "asynchronous advantage actor-critic" model, which makes additional use of "experience replay"	• The focus is again on the price component, which must be optimized first and foremost • Electric vehicles pose a certain challenge because they can disconnect from the microgrid at any time → Electric vehicles were explicitly not considered in the paper
Applications of reinforcement learning in energy systems (Link)	• Paper is a literature review on reinforcement learning managing power systems • State-of-the-art methods such as Actor-Critic were rarely used in experiments, which according to the authors, resulted in severe performance degradation • Multi-agent RL does offer a lot of potential, finding solutions to complex interaction problems between multiple parties → nevertheless, certain methods from this field were not used • Conclusion: RL has a lot of potential to solve power distribution problems efficiently	

Titel	Approach	Difference to our use case
Deep Reinforcement Learning for Smart Home Energy Management (Link)	• Energy cost minimization for a smart home without a model of the building's thermal dynamics considering a comfortable temperature range • Energy-related challenges: Renewable energy performance, non-shiftable electricity demand, outdoor temperature, and electricity price • Energy system owns storage, consumers and generators • Within an experiment, a Markov decision process and a Deep Deterministic Policy Gradients (DDPG) were implemented and compared to each other • According to the authors, DDPG is comparatively effective and robust	• Consumers are permanently connected to the power grid not like electric vehicles • Cost minimization is again in the foreground

Smart Grid Optimization by Deep Reinforcement Learning over Discrete and Continuous Action Space (Link)	• Comparison of procedures for discrete and continuous action spaces that pursue the goal of meeting energy needs by means of different energy suppliers (external & internal).	• the goal of the model proposed by the authors is only to decide to buy or sell energy (in the continuous action space: how much to buy or sell) → not compatible with our problem definition

Titel	Approach	Difference to our use case
Deep Reinforcement Learning for Optimal Energy Management of Multi-energy Smart Grids (Link)	• Deep reinforcement learning approach for optimal control of multi-energy systems in smart grids. • The multi-energy residential microgrid model used here consists of electricity, heating and cooling storage, and thermal production systems and renewable energy generation • Challenge: optimal real-time control of multi-energy systems with multiple simultaneous continuous action spaces. • A DDPG algorithm was tested in an experiment. • It was found that the DDPG agent can handle continuous state and action spaces well	• No consideration of electric vehicles