

A general intro to the course

Industrial IoT for Digitization of Electronic Assets

Prof. Tomislav Dragičević

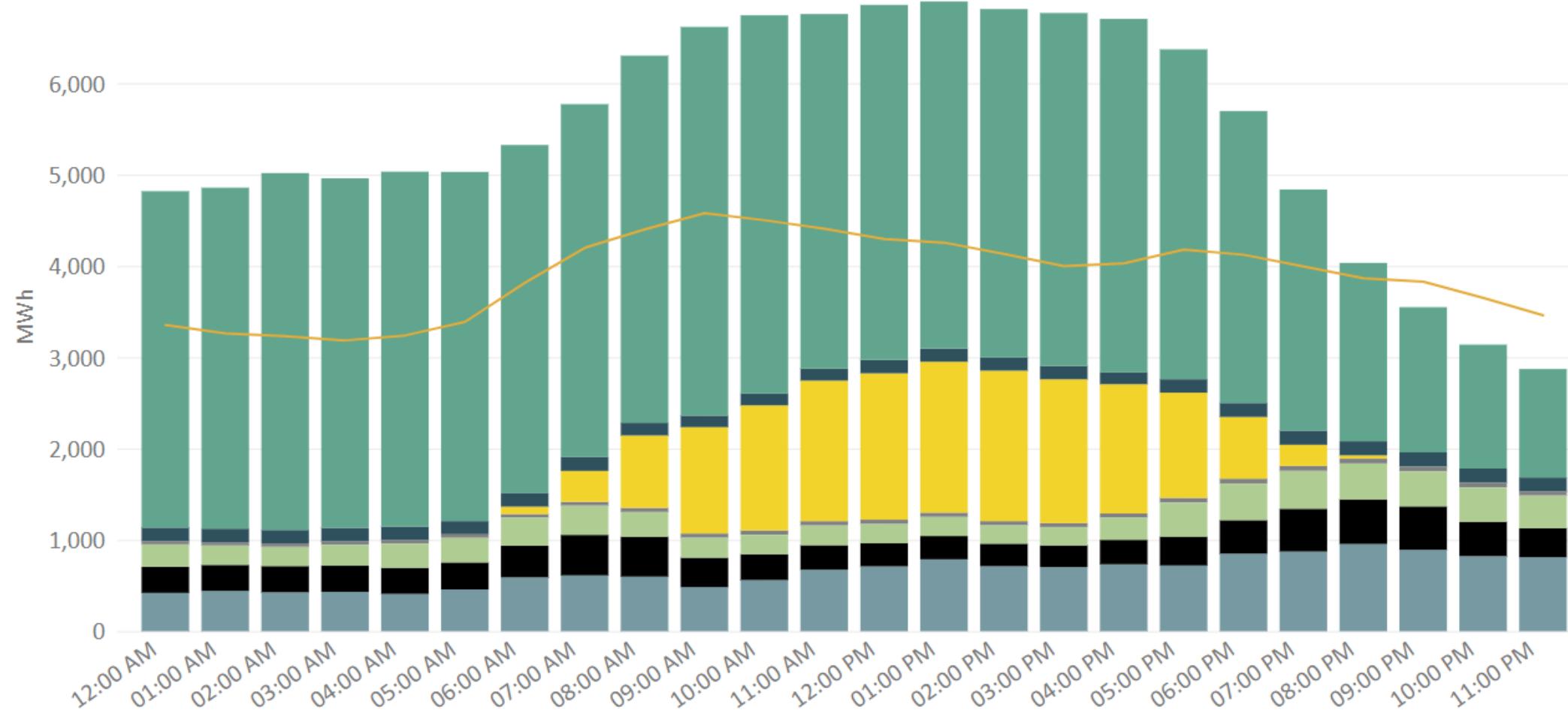
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TOTAL PRODUCTION

Total danish electricity production

Energy Source ● Biomass ● Coal ● Fossil gas ● Hydro power ● Oil ● Other renewable ● Solar power ● Waste ● Wind power ● Consumption



Last 24 hours

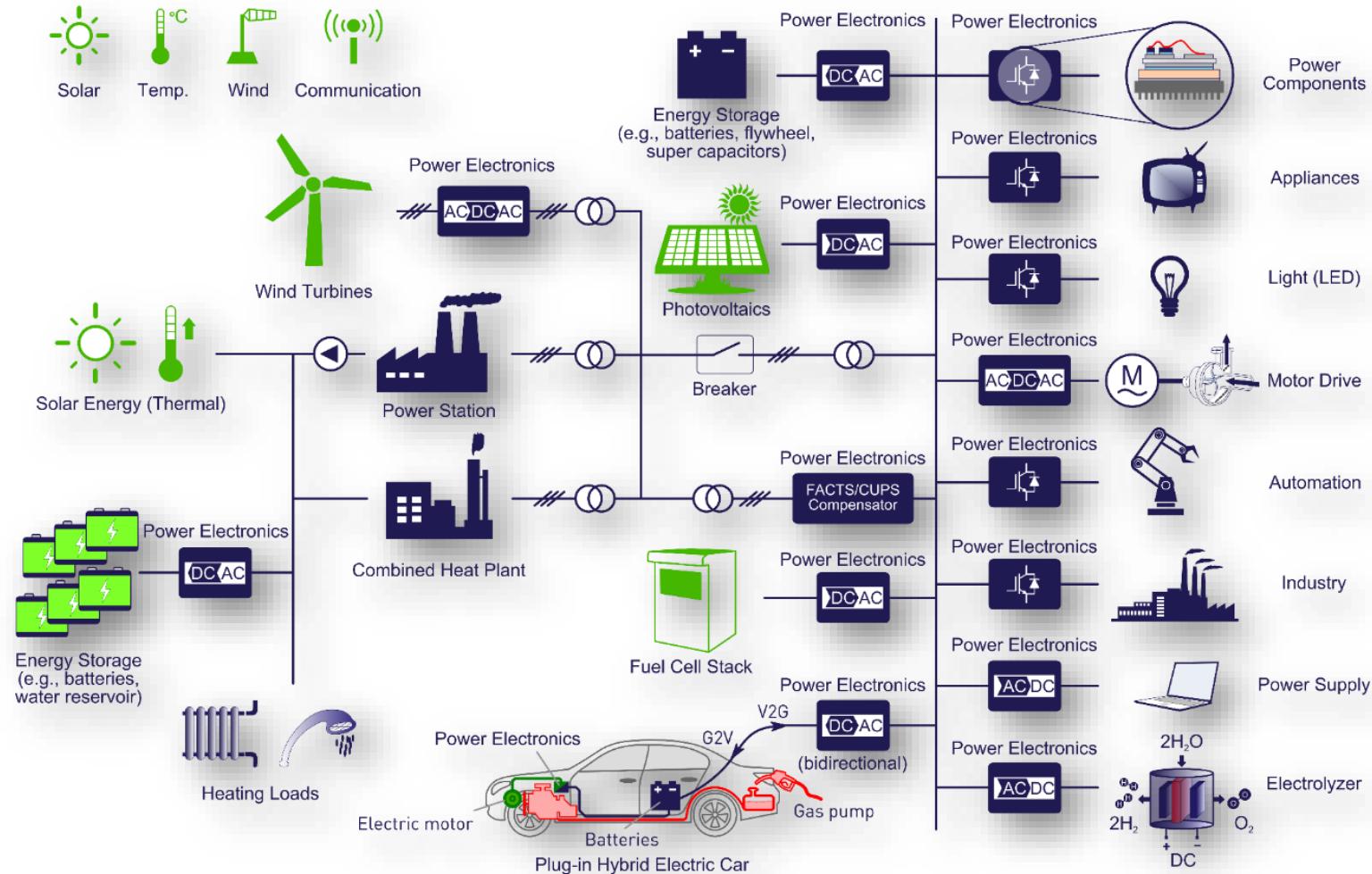
Last 30 days

Last 12 months

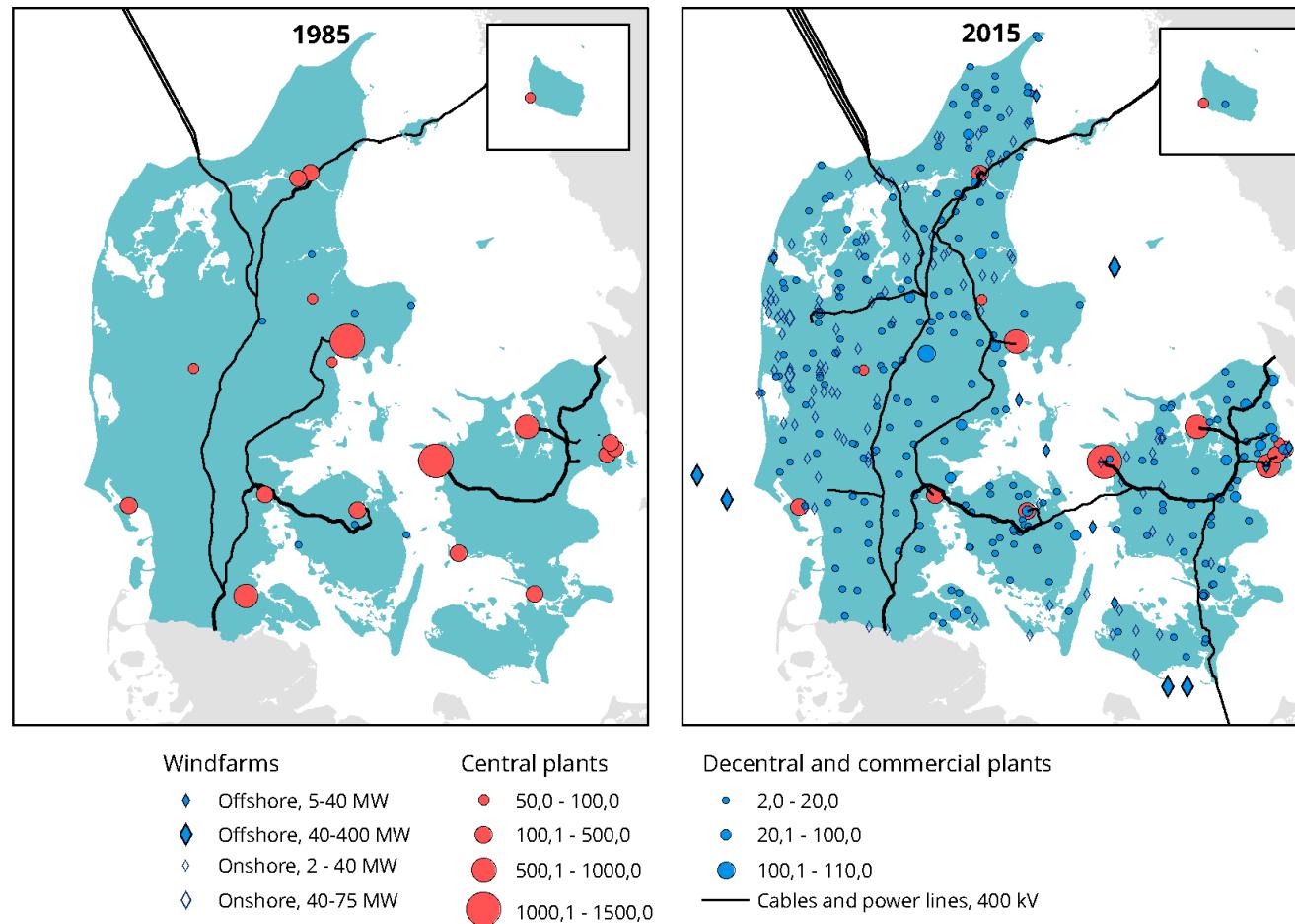
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ENERGINET

Power Electronics Centered

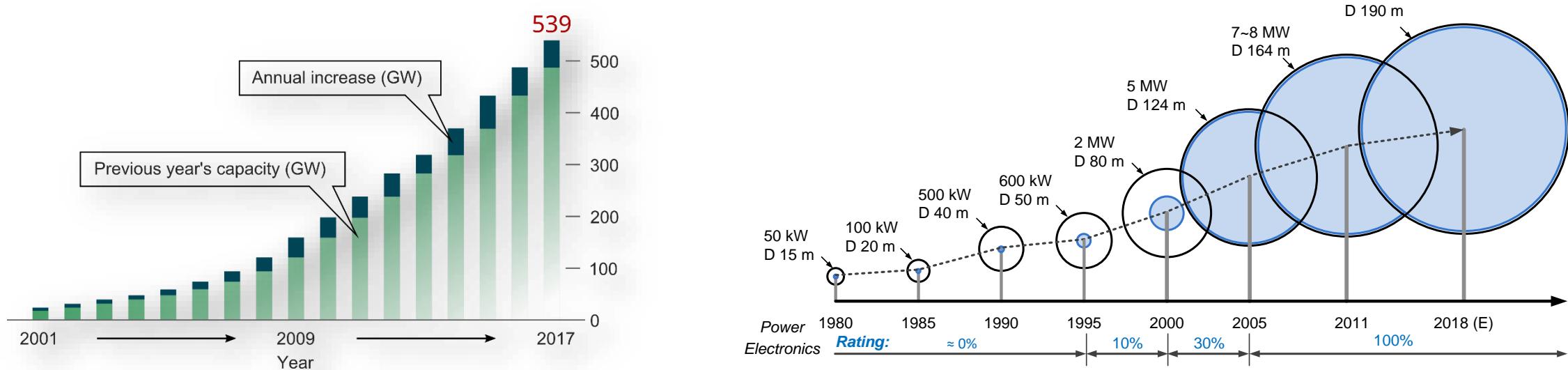


Development of Electric Power System in Denmark



From Central to De-central Power Generation

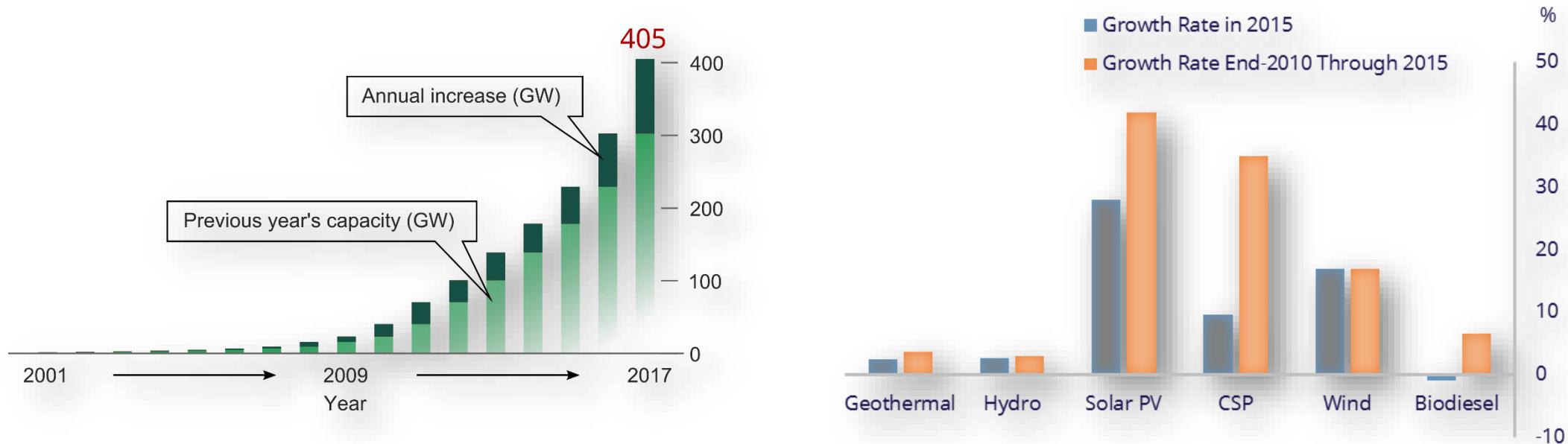
State of the Art Development – Wind Power



Global installed wind capacity (until 2017): **539 GW**, 2017: **52.3 GW**

- Higher total capacity (+50% non-hydro renewables).
- Larger individual size (average 1.8 MW, up to 6-8 MW, even 10 MW).
- More power electronics involved (up to 100 % rating coverage).

State of the Art Development – Photovoltaic Power



Global installed solar PV capacity (until 2017): 405 GW, 2017: 102 GW

- More significant total capacity (29 % non-hydro renewables).
- Fastest growth rate (42 % between 2010-2015).

Our facilities at DTU



Smart Converter Lab



Control Center Lab



High Power Lab



Electric Vehicle Lab

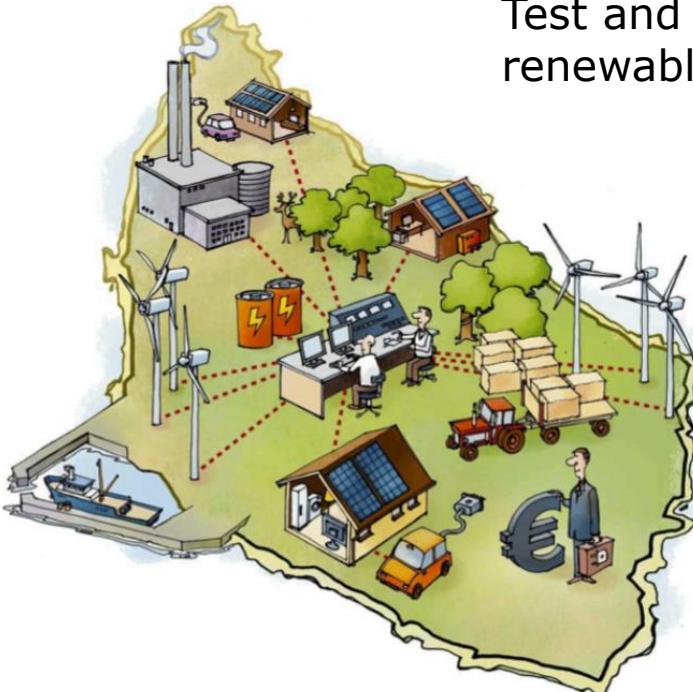


High Voltage Lab



Electric Lab

Smart Community Bornholm



Test and demonstration in full-scale renewable energy laboratory

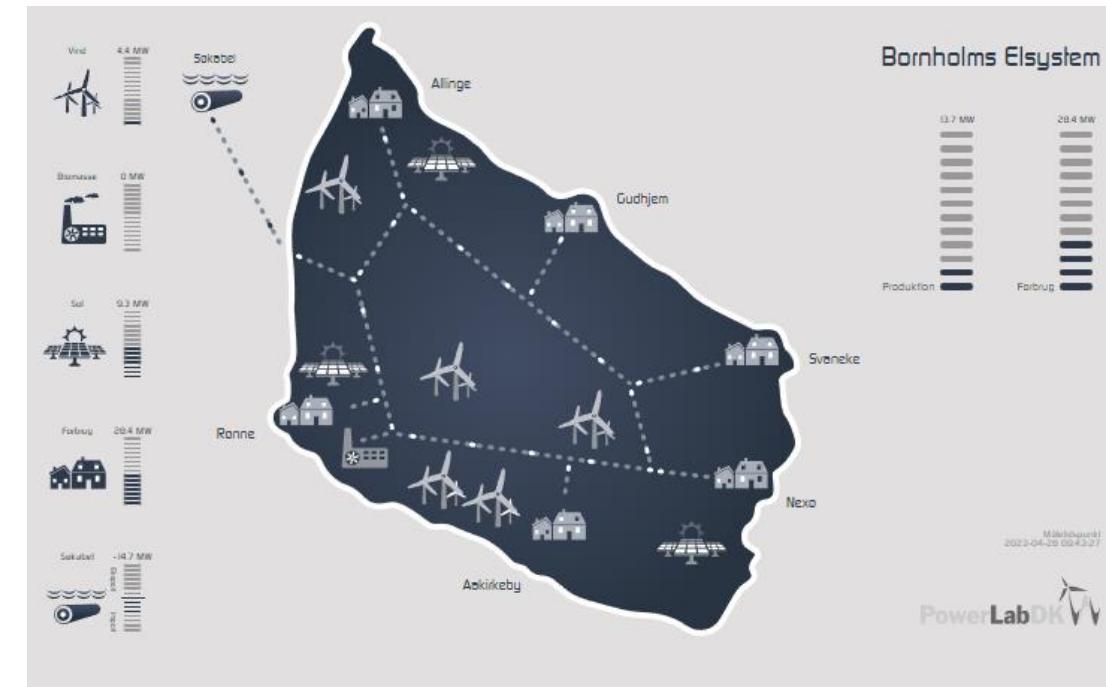
Generators	
1 CHP steam turbine (wood/coal/oil chips)	37 MW
35 wind turbines	30 MW
SOLAR PV (2012)	5 MW
2 gas engines (biogas)	2 MW
14 backup diesel generators (oil)	34 MW
1 backup steam turbine (oil)	25 MW
Electric vehicles (under roll-out)	

Grid	
60 kV grid	131 km
Number of 60/10 kV substations	16
10 kV grid	927 km
Number of 10/0.4 kV substations	1039
0.4 kV grid	1913 km

District heating	
Number of district heating systems	5
Total heat demand (in 2007)	560 GWh
Normal operation mode	Interconnected Nordel

Customers	
Number of customers	~28.000
Number of customers (> 100.000 kWh/year)	~300
Total energy consumed	250 GWh
Peak load	55 MW

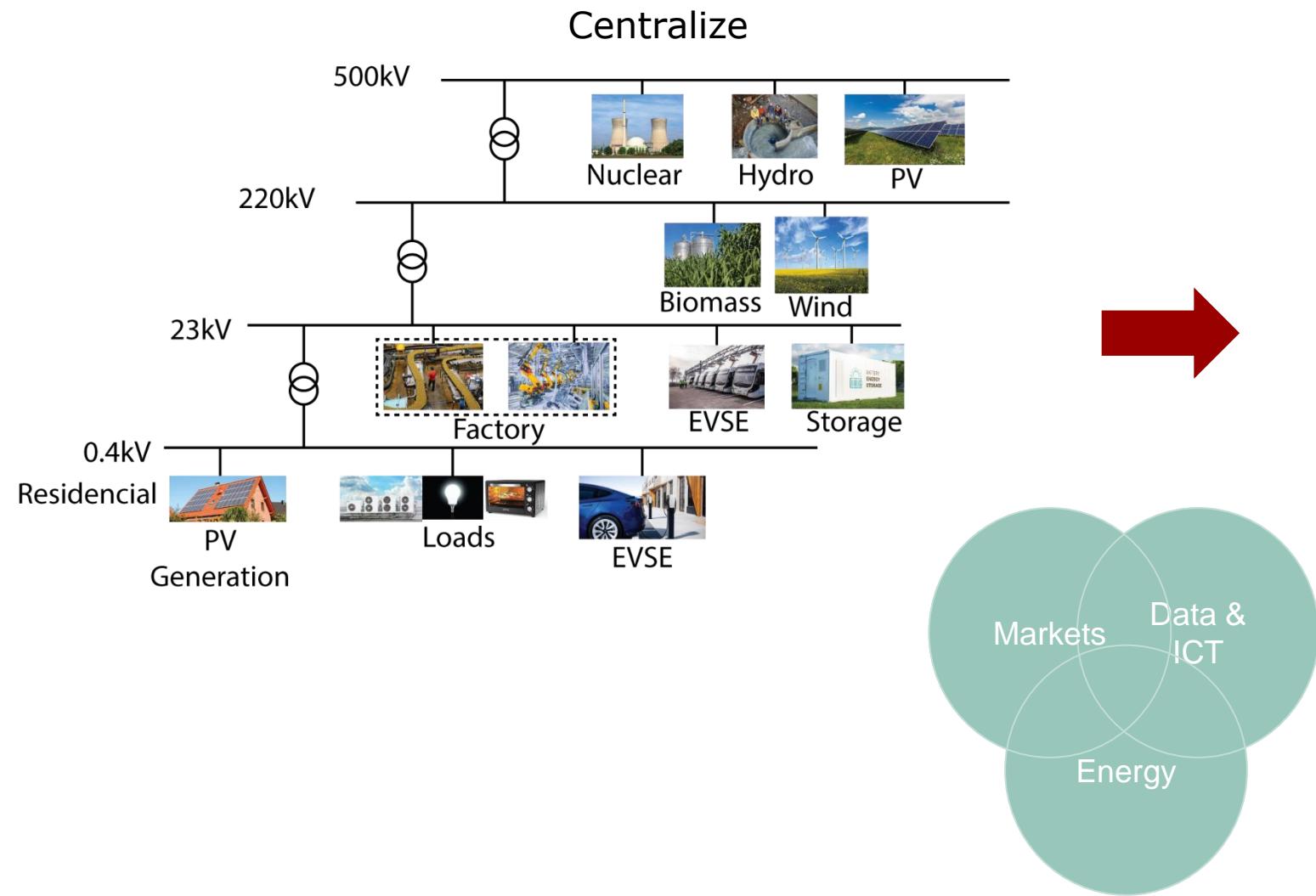
Equivalent to 1% of Denmark concerning area, population, and energy consumption.



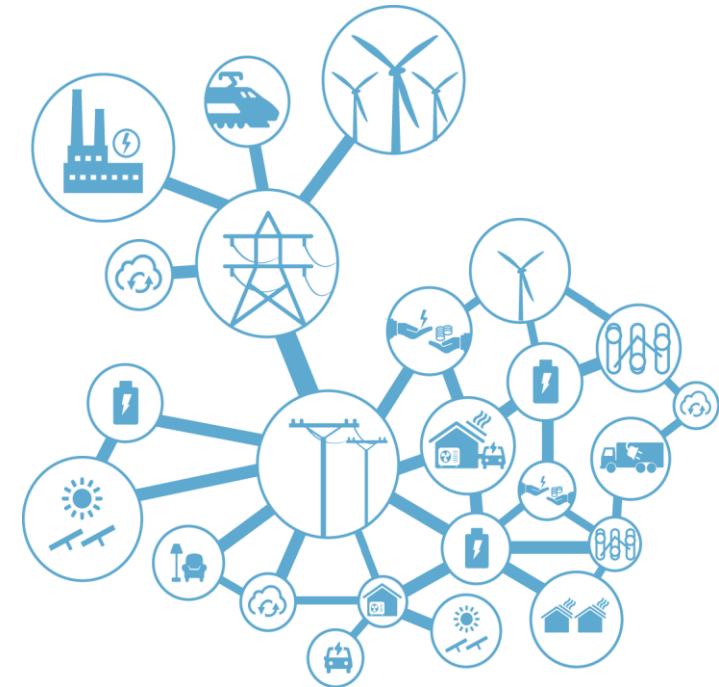
<https://www.powerlab.dk/facilities/bornholmpowersystem>

Motivation for the course

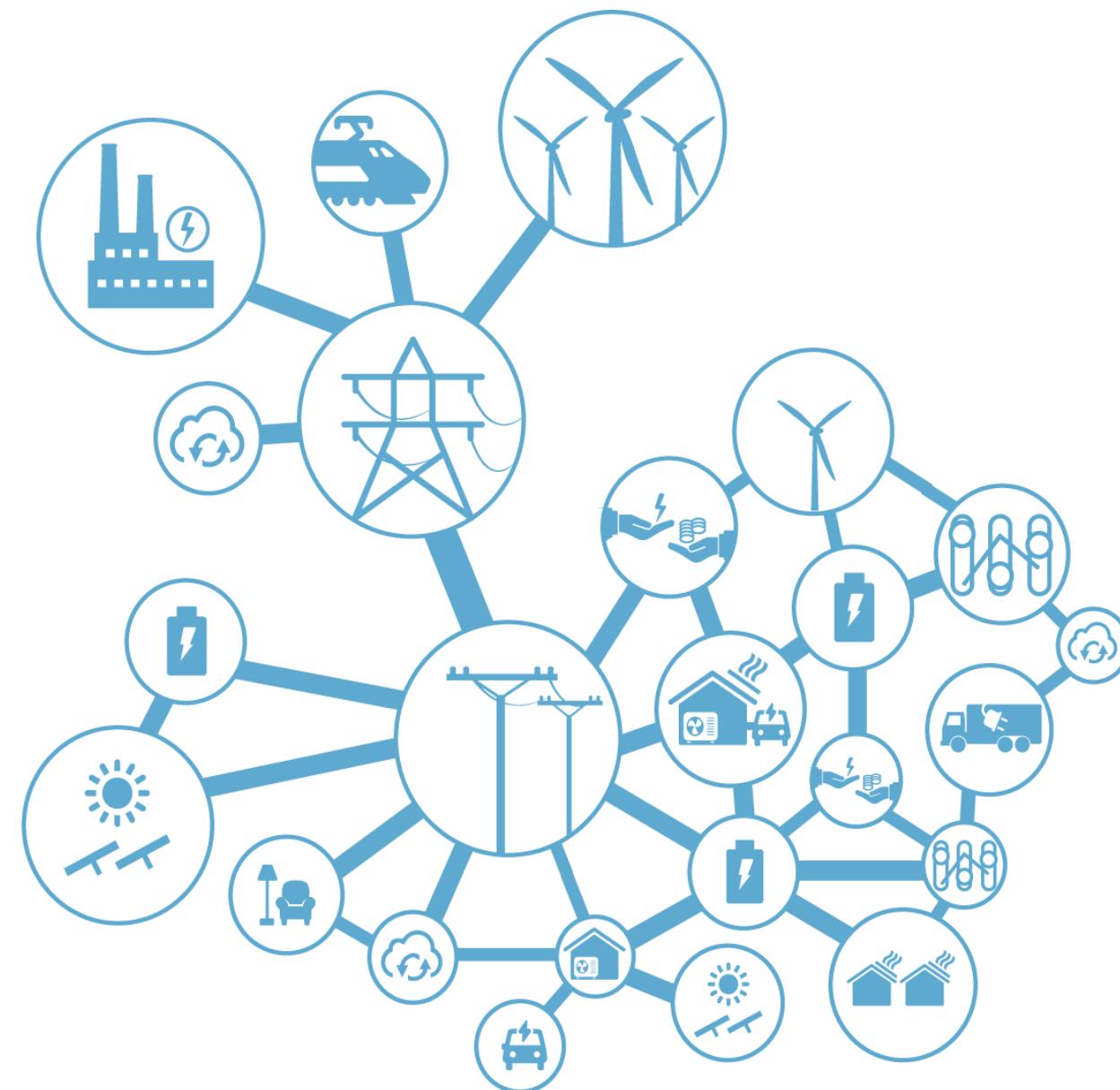
Motivation

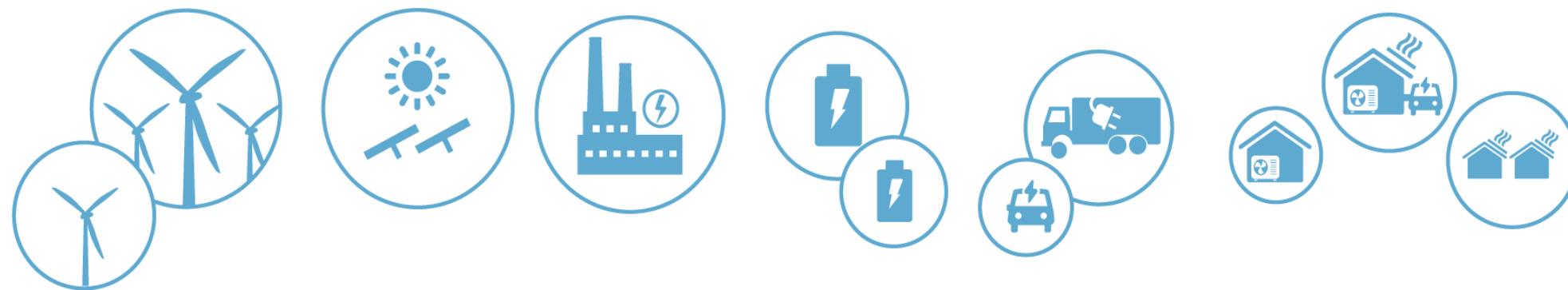


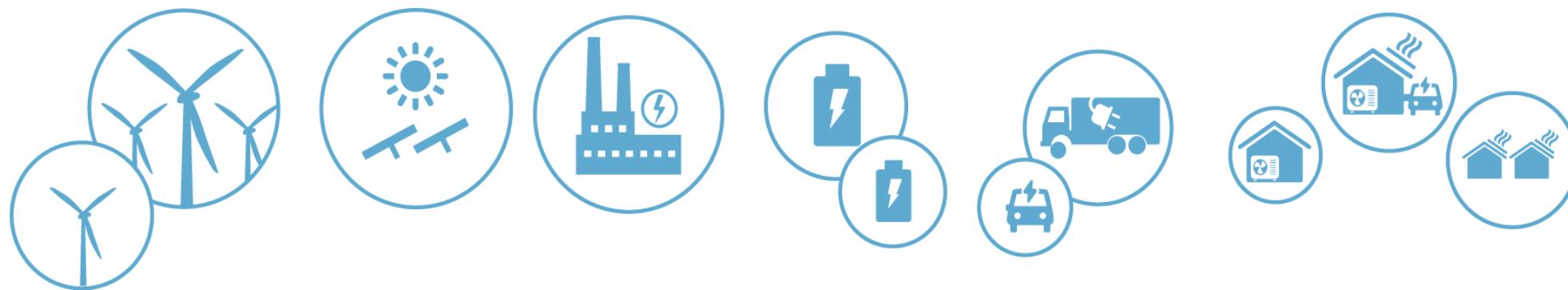
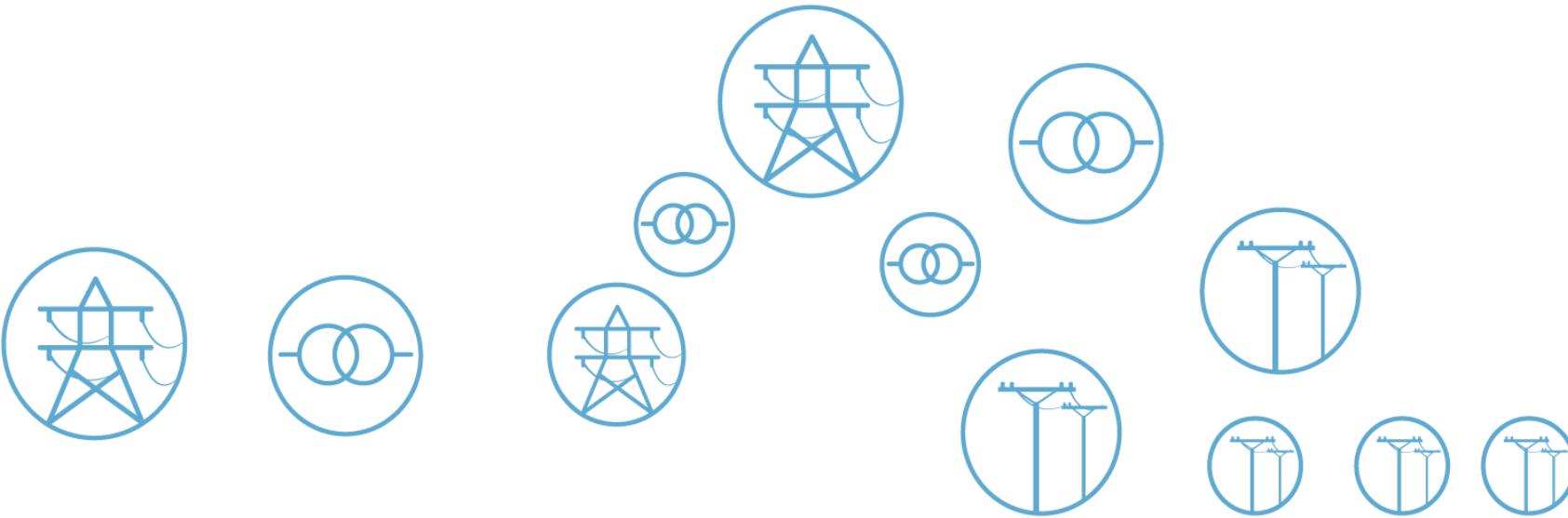
Decentralize

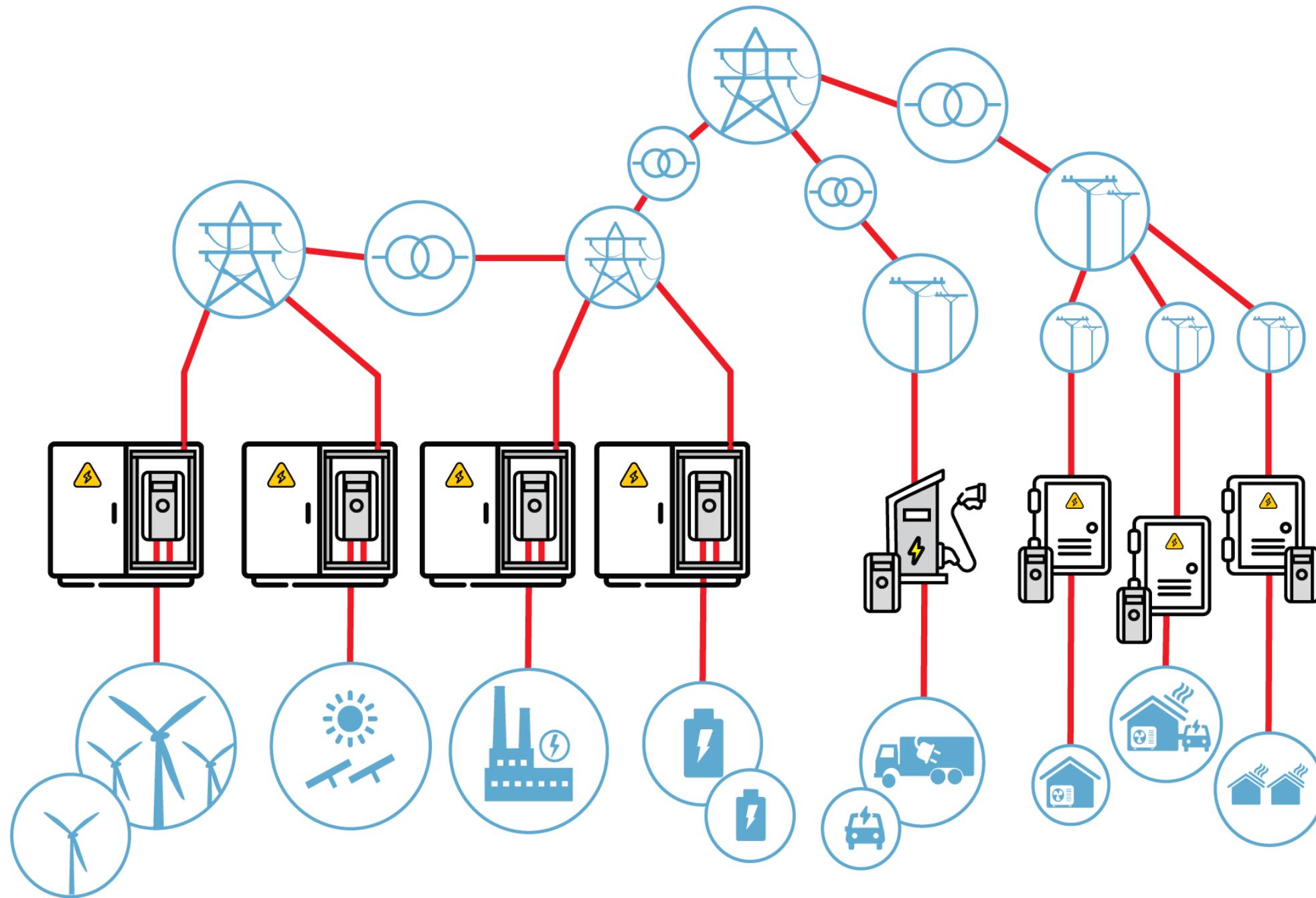


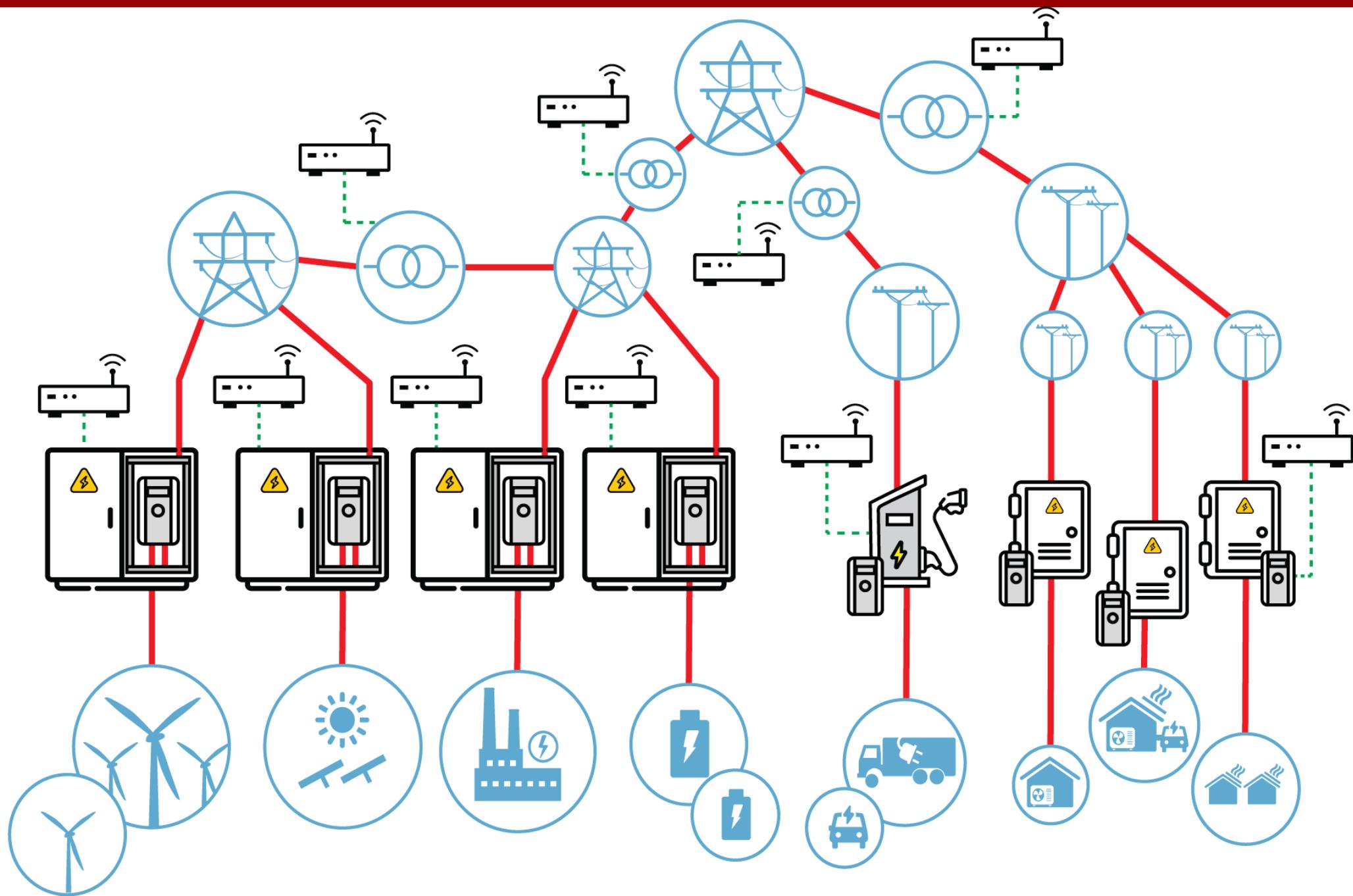
Digitalization











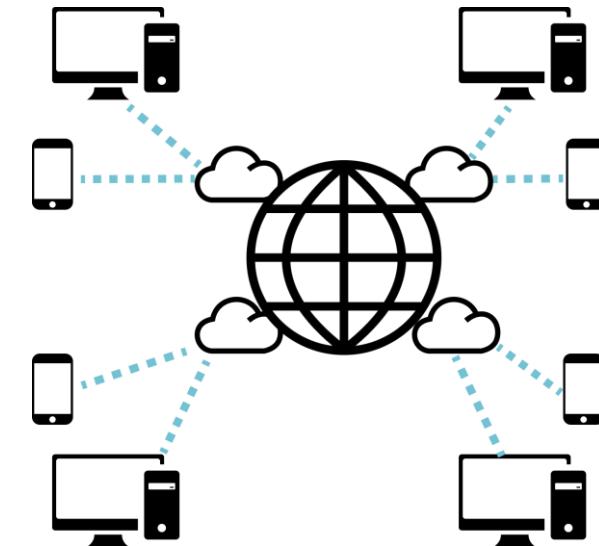
What is the Cloud?

Servers that are accessed over the Internet, along with the software and databases that run on those servers.

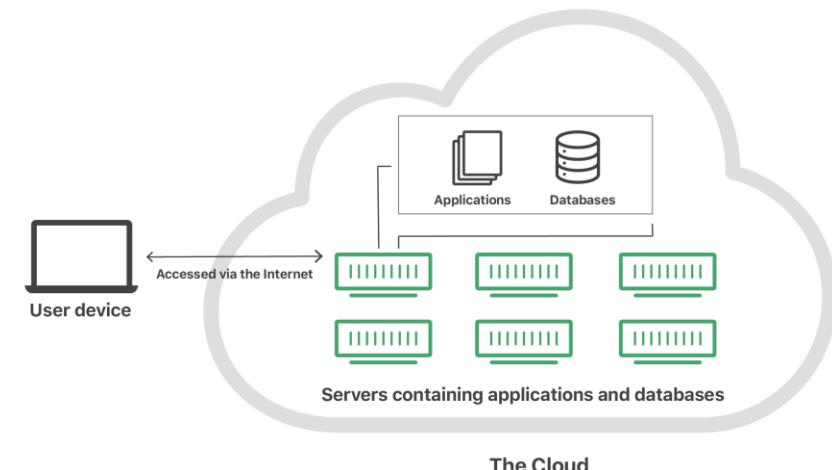


Cloud servers are located in data centers all over the world.

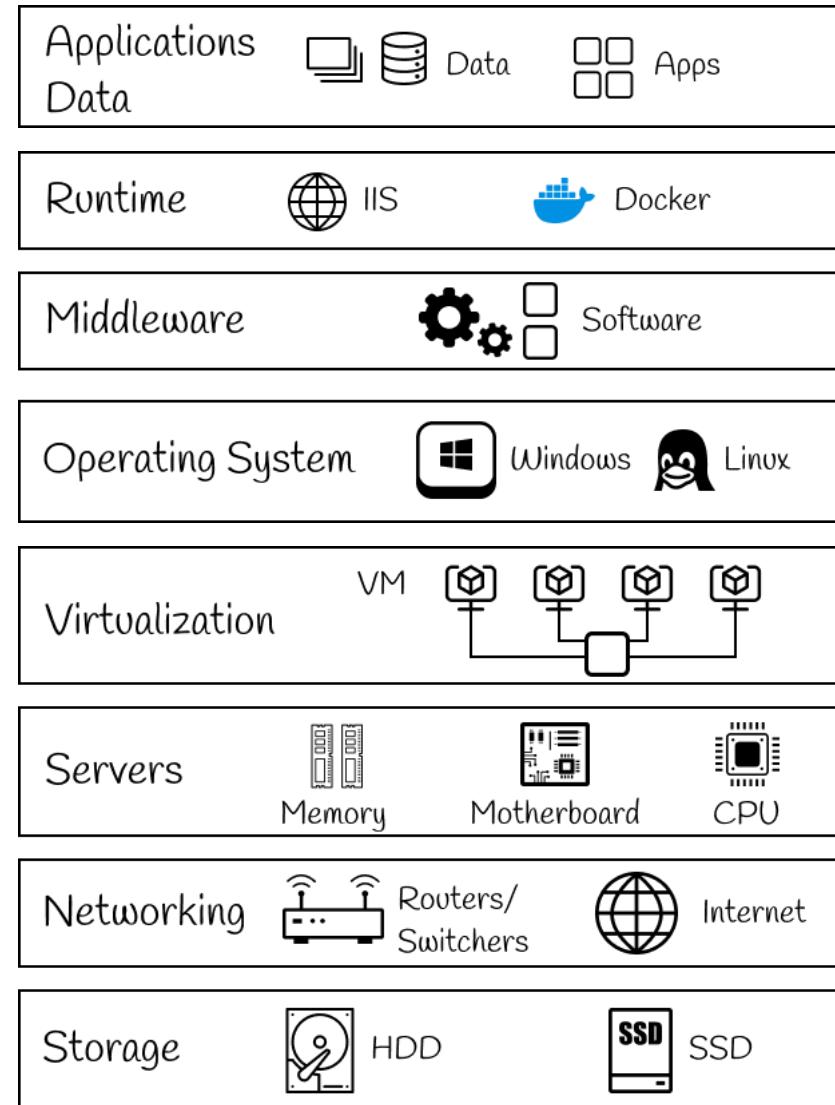
The computing and storage takes place on servers in a data center, instead of locally on the user device.



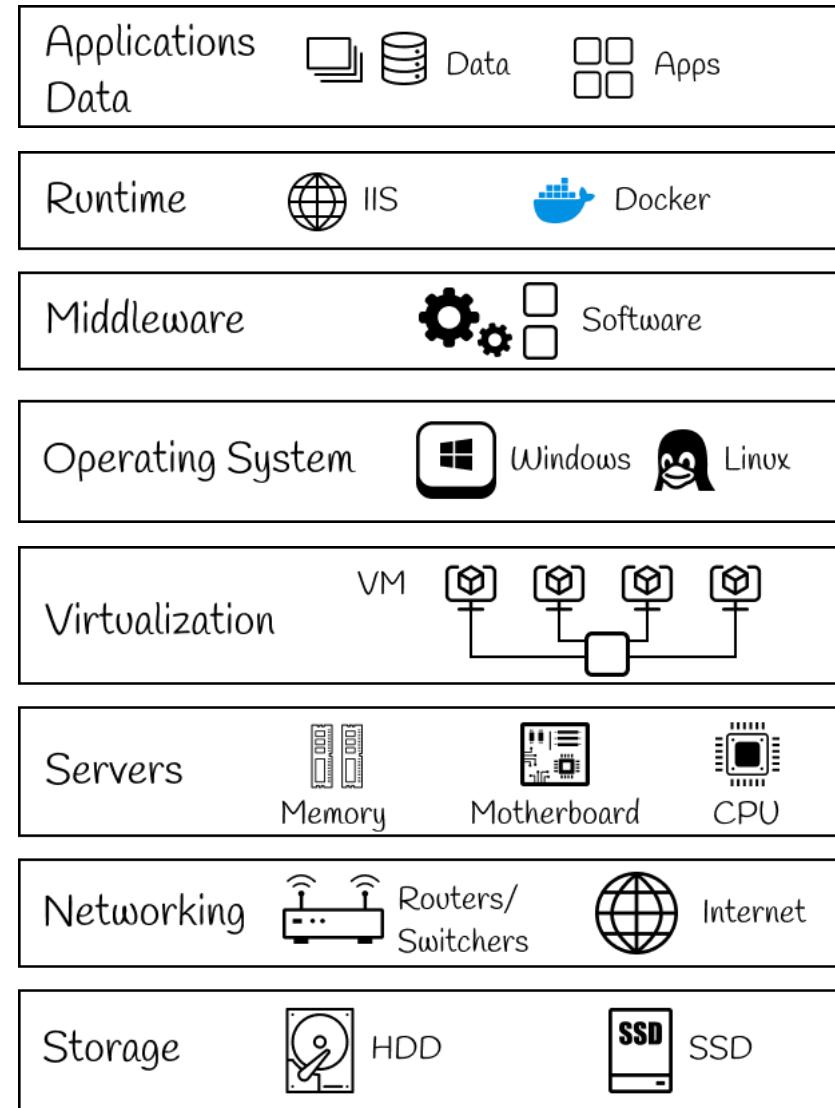
Users and companies do not have to manage physical servers themselves or run software applications on their own machines.



Cloud Service Model

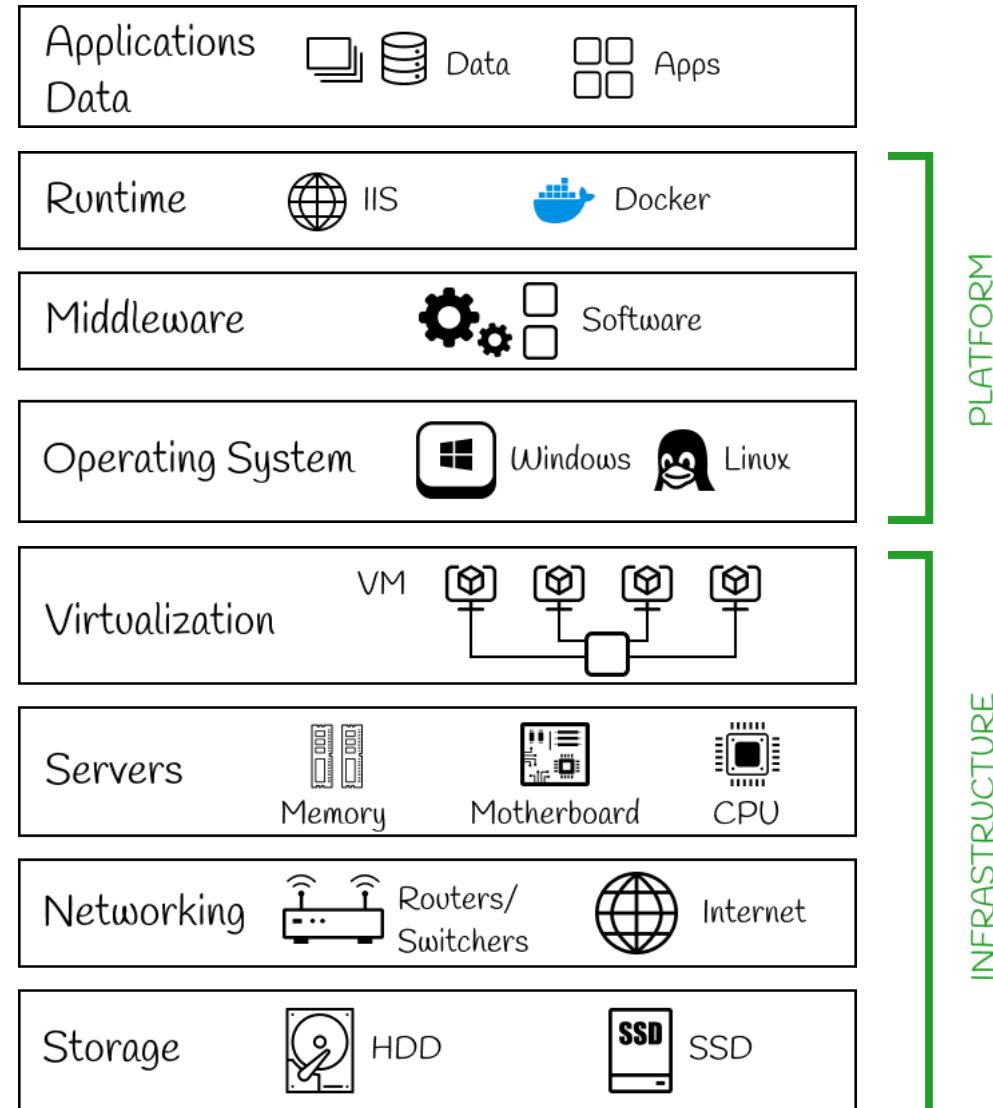


Cloud Service Model



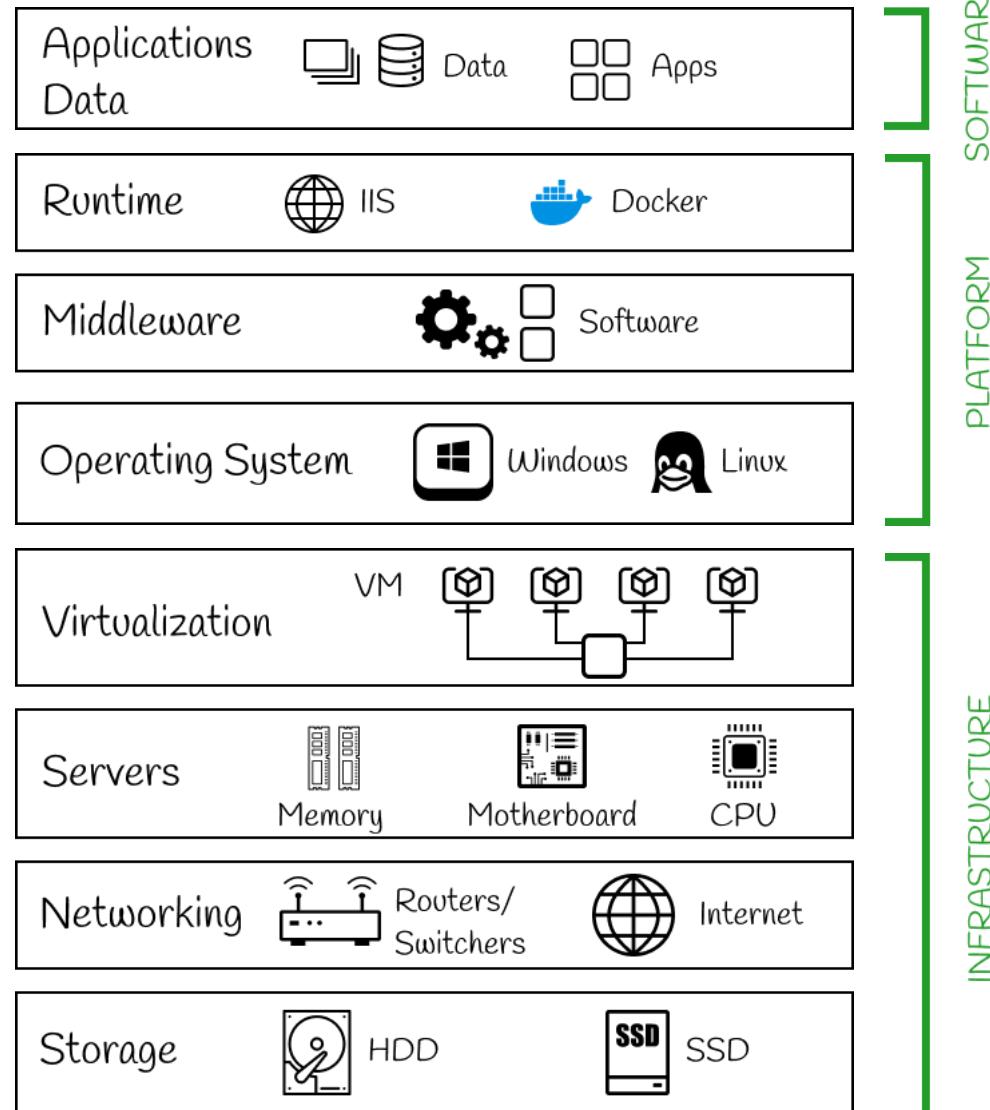
Layers related with the hardware and virtualization

Cloud Service Model



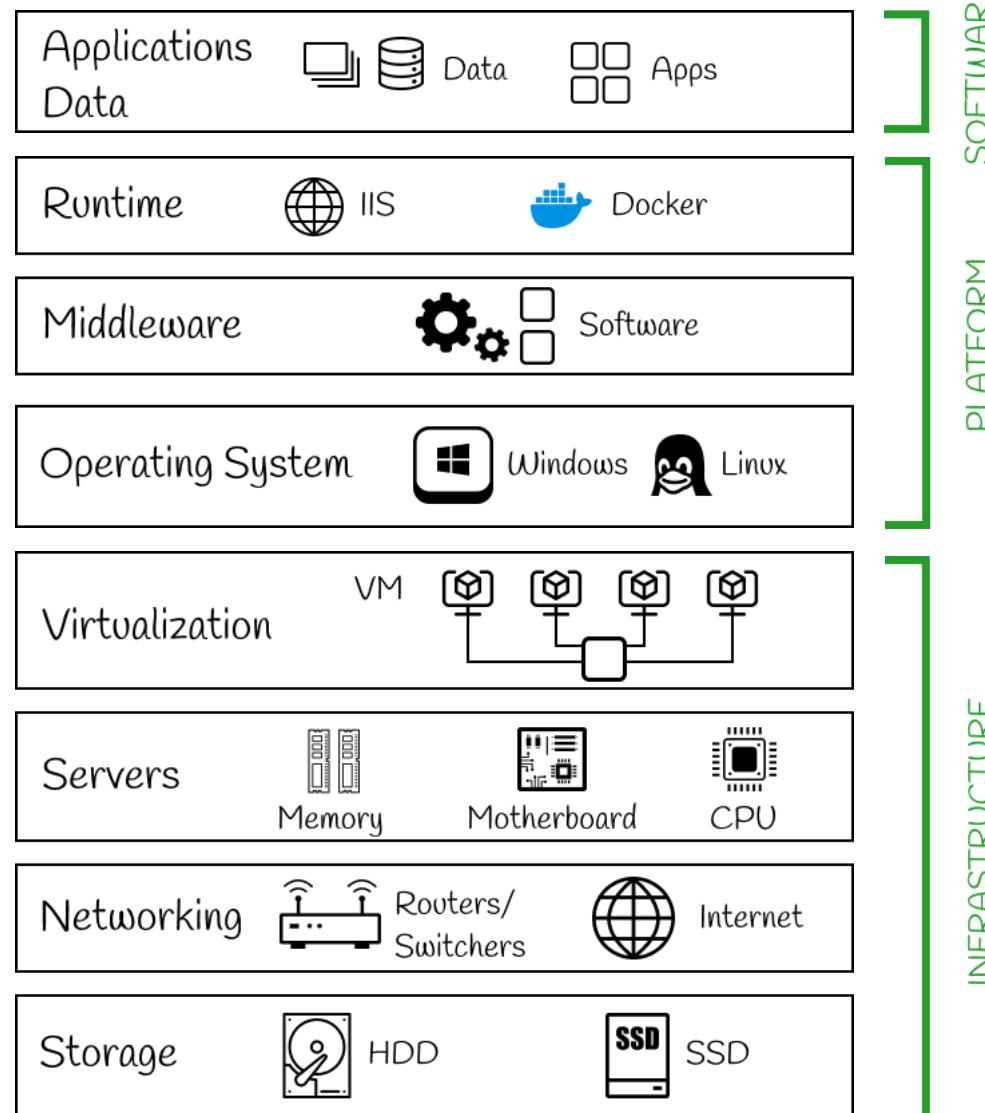
Layers related with the system and configuration that is required for you to run the application.

Cloud Service Model

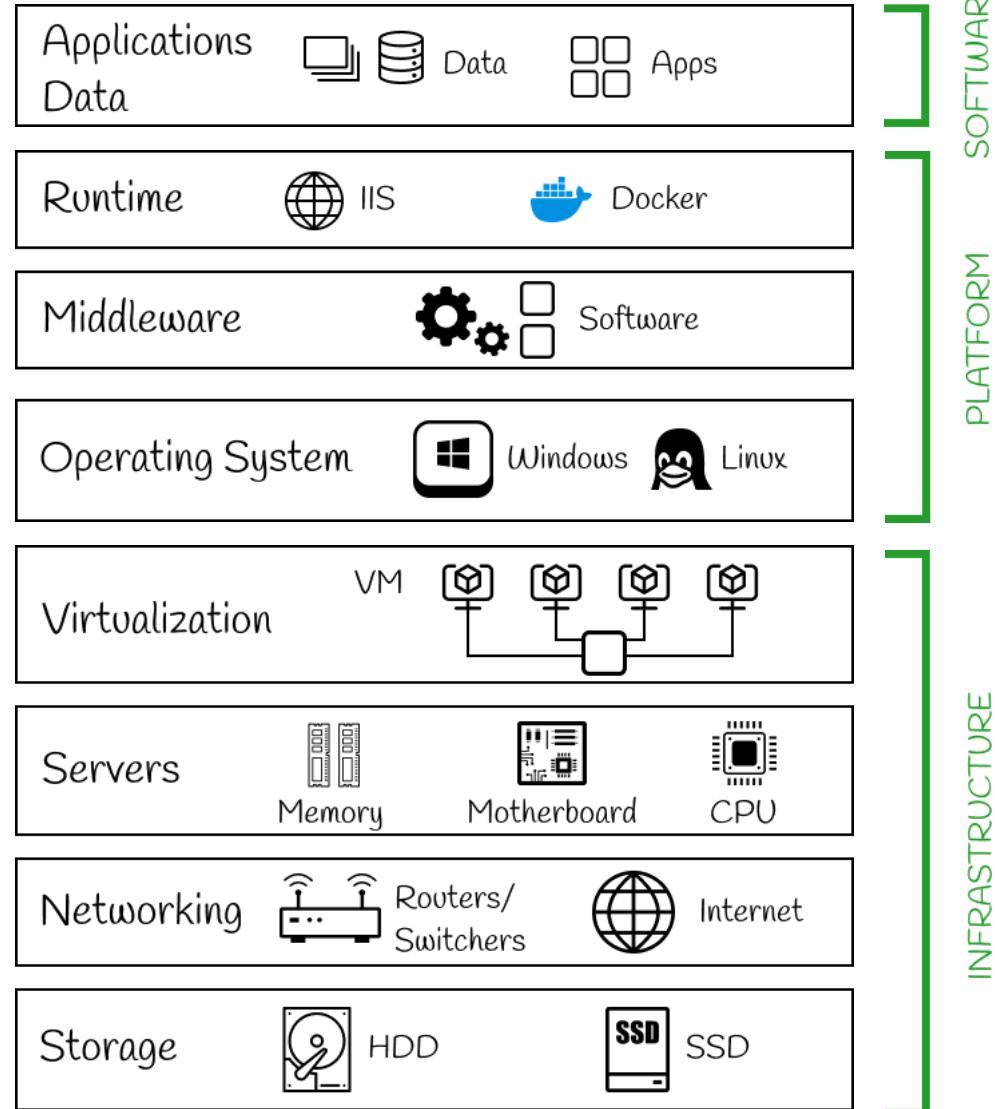


Layer related with the application itself.

Cloud Service Model

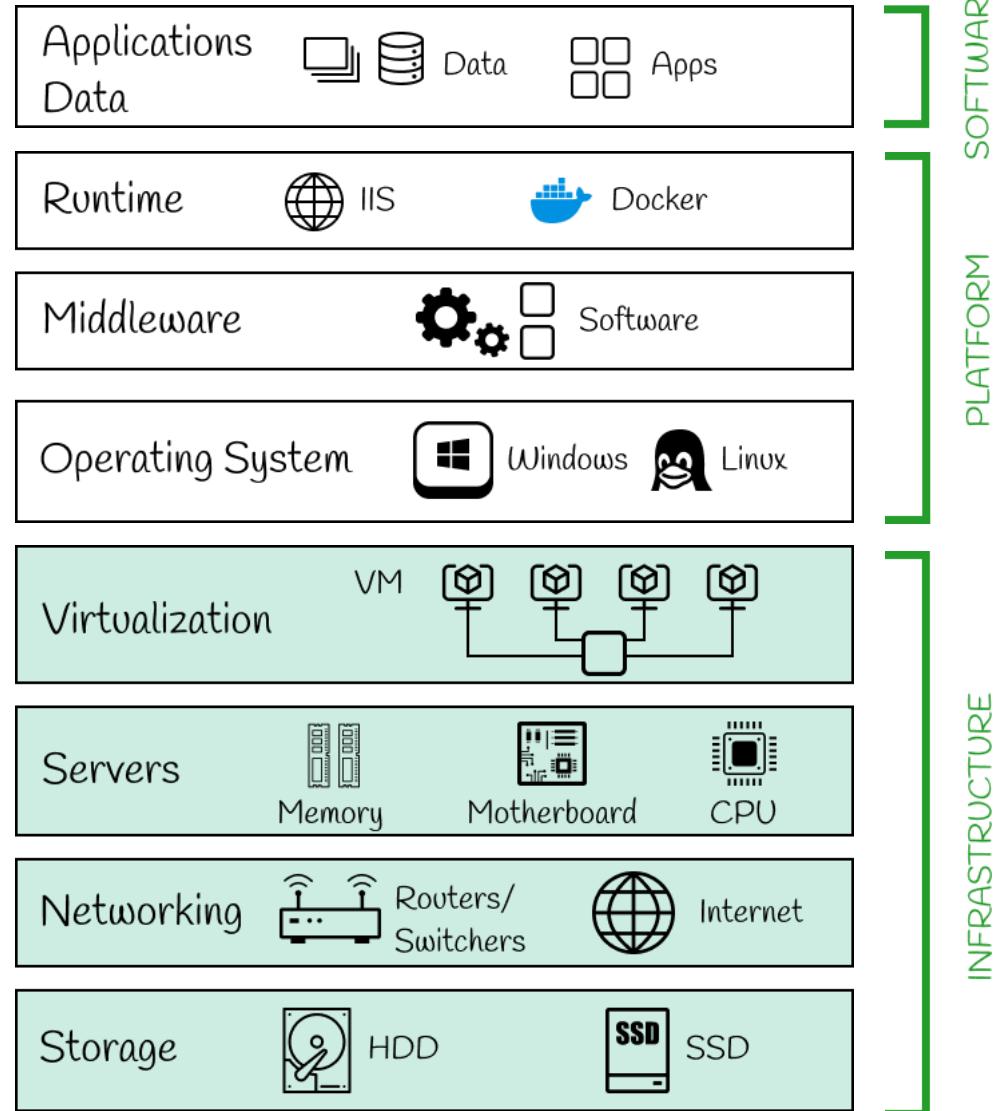


Cloud Service Model



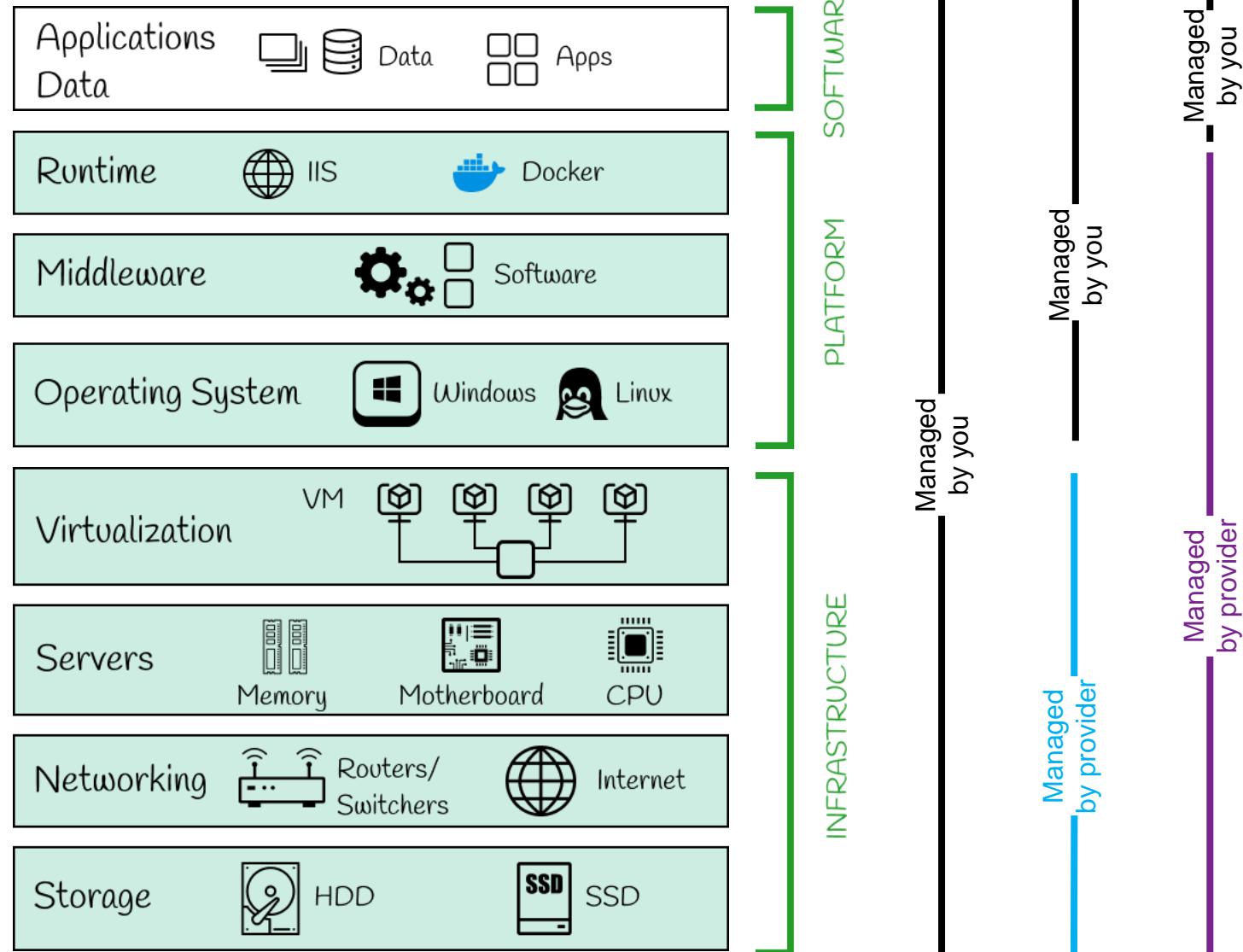
Who manages?

Cloud Service Model

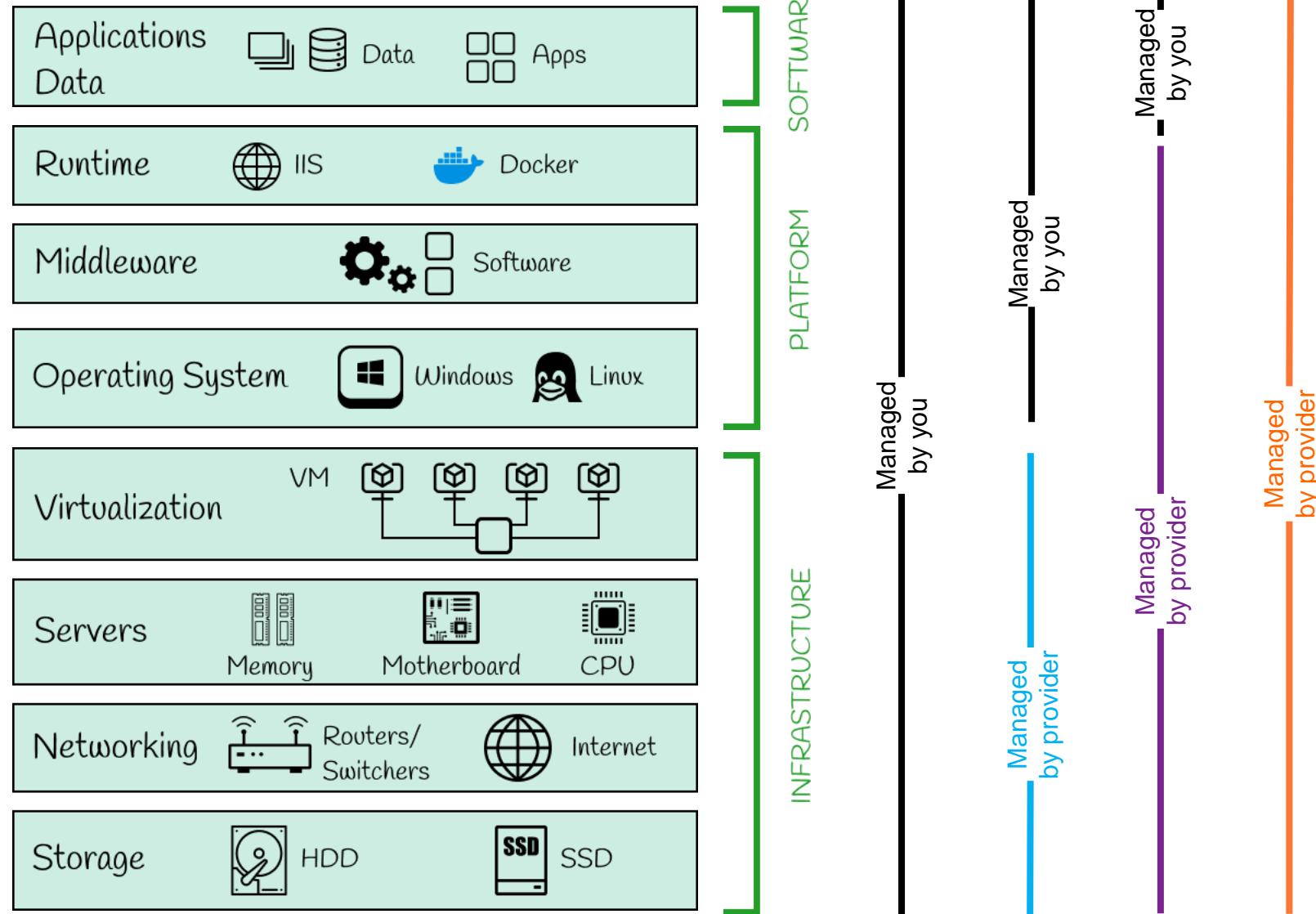


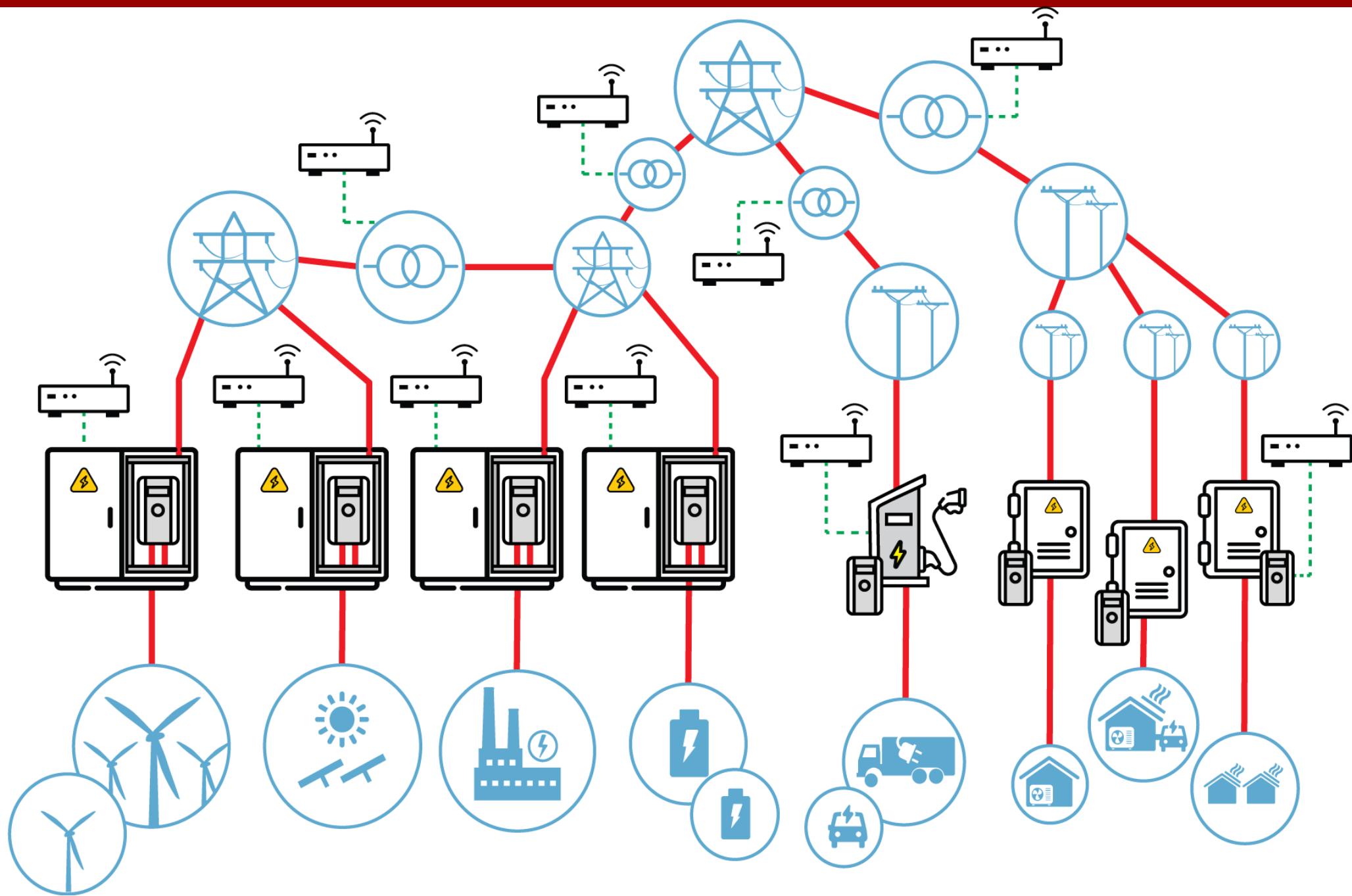
Who manages?

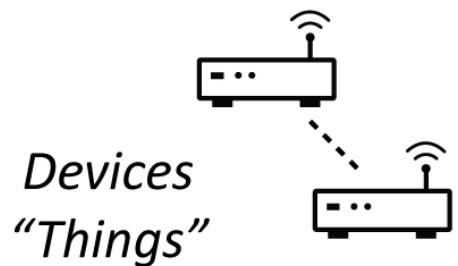
Cloud Service Model

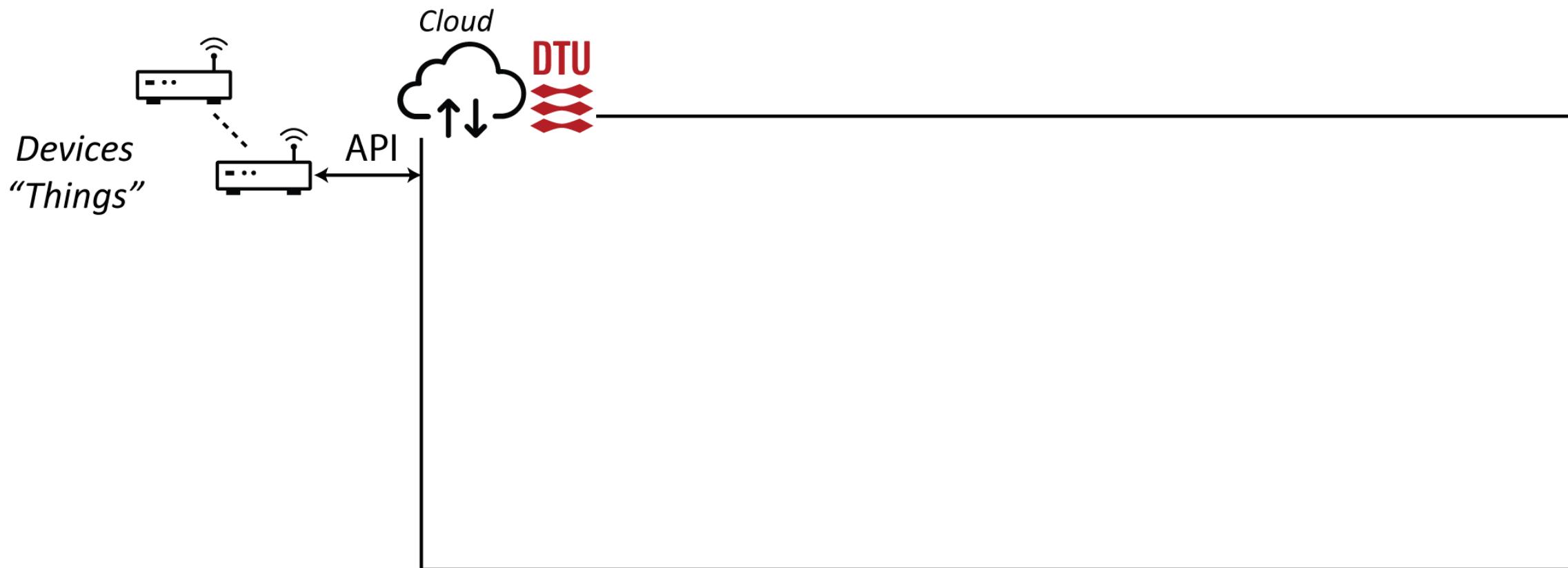


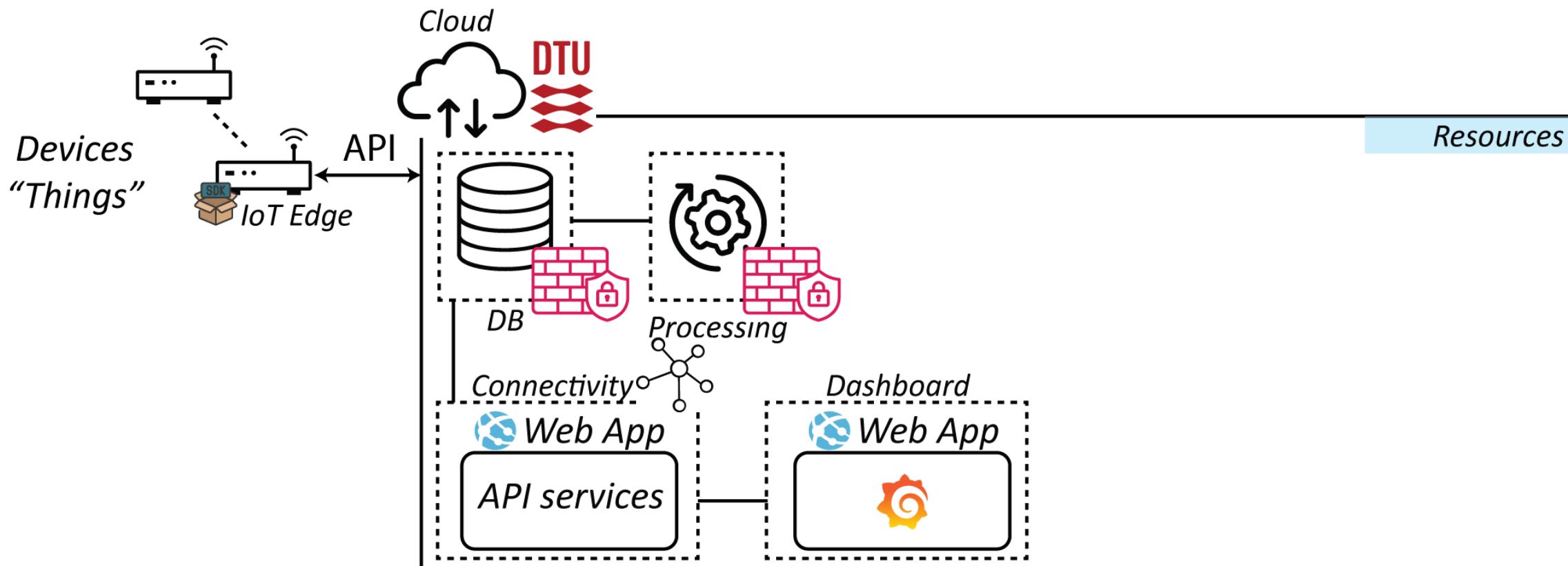
Cloud Service Model

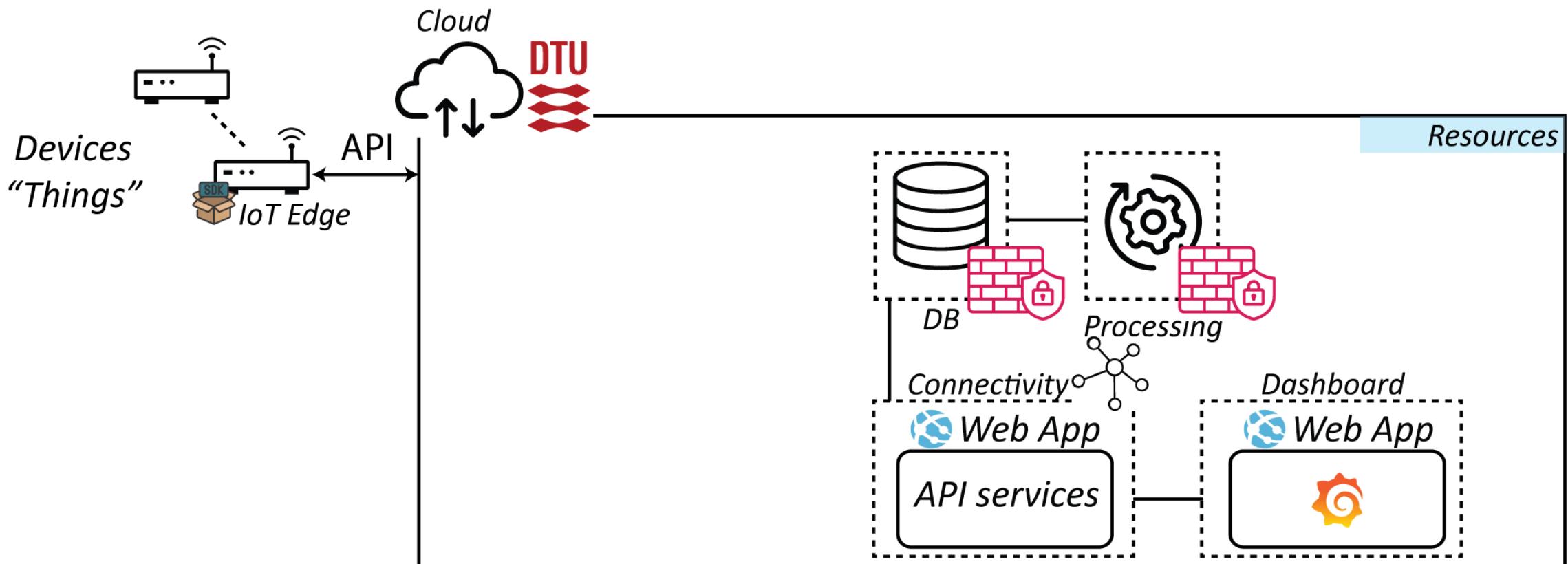


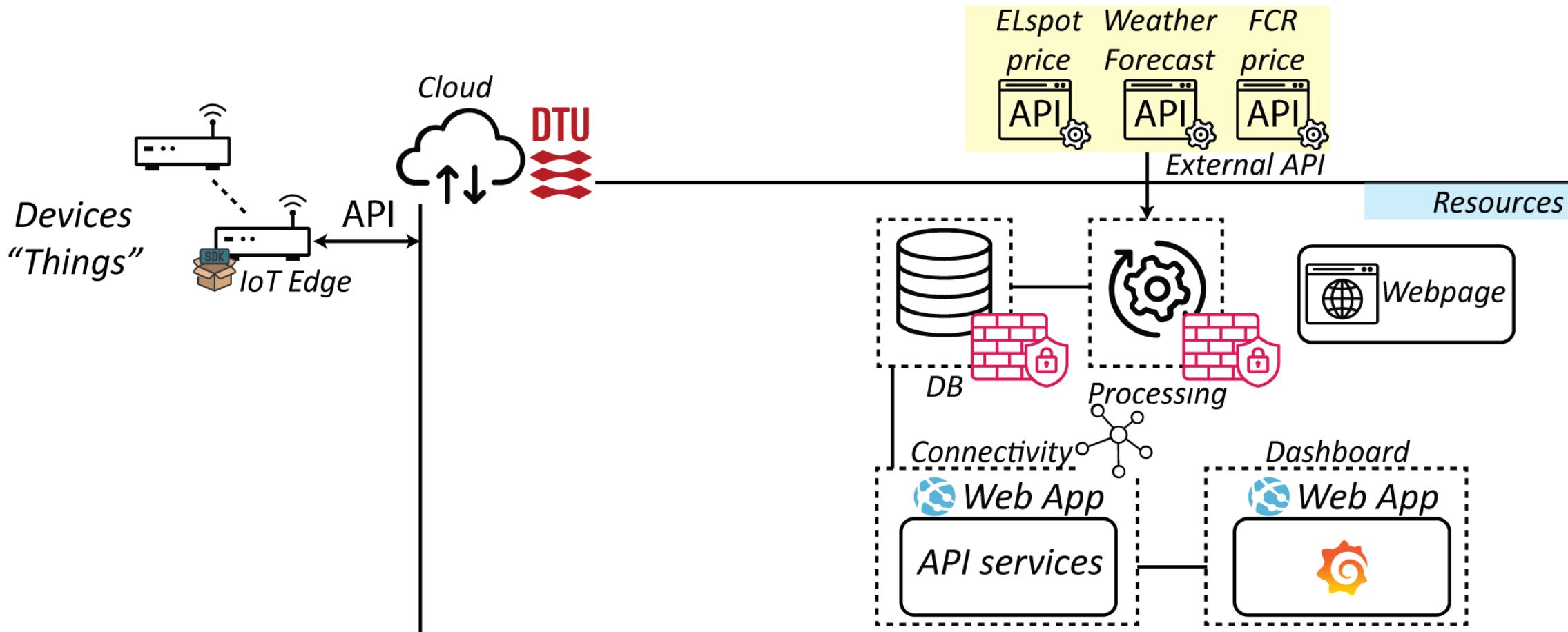


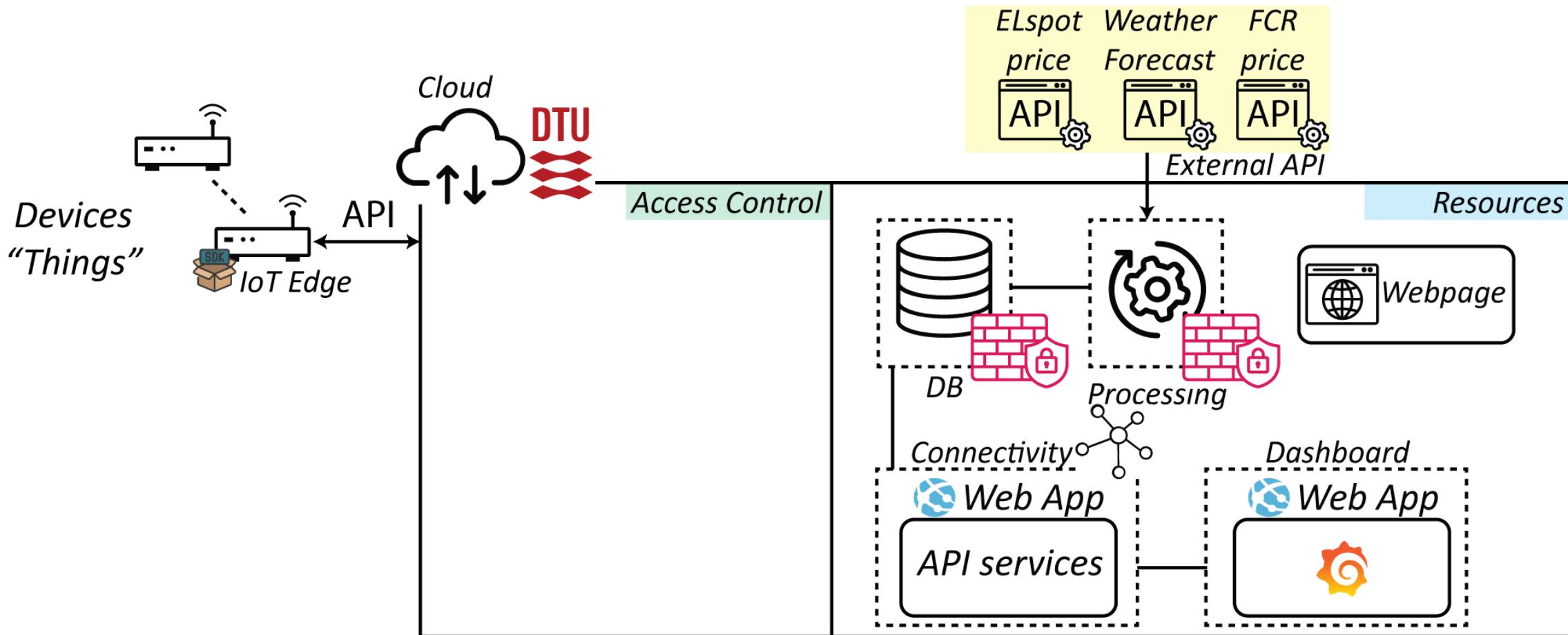


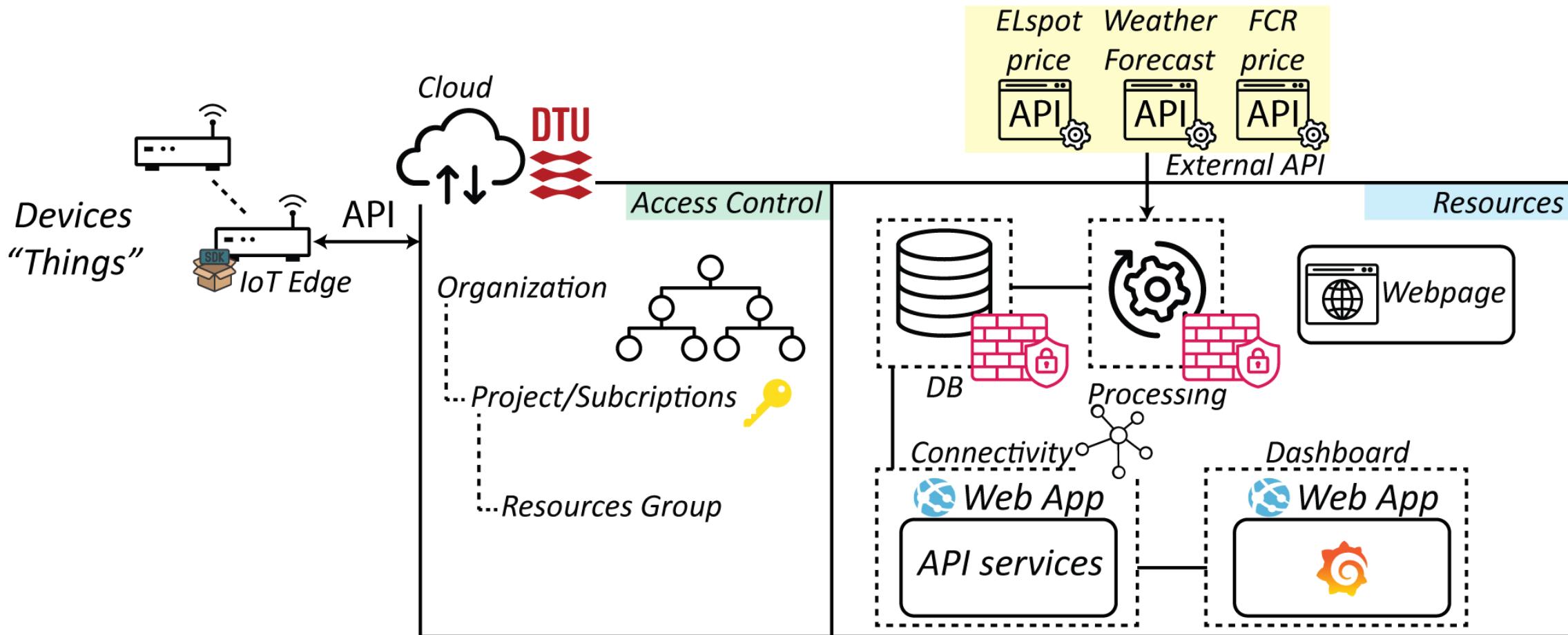


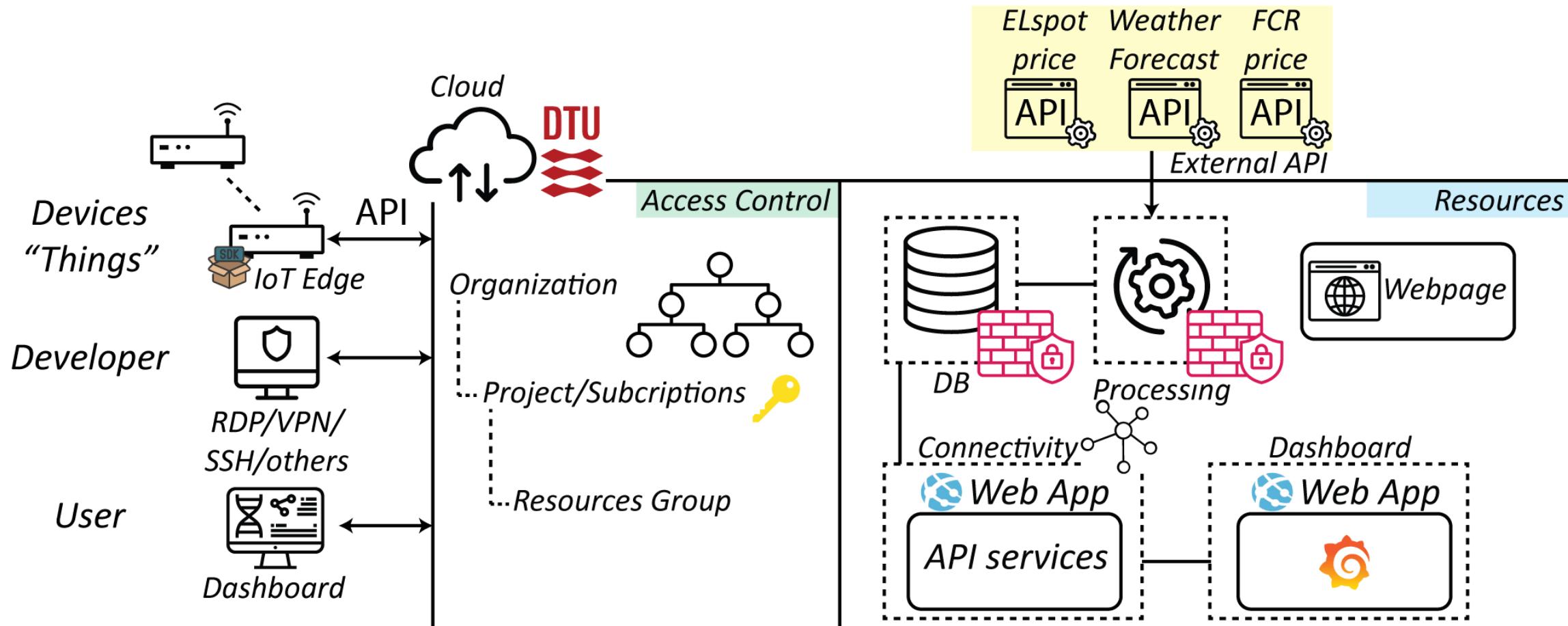






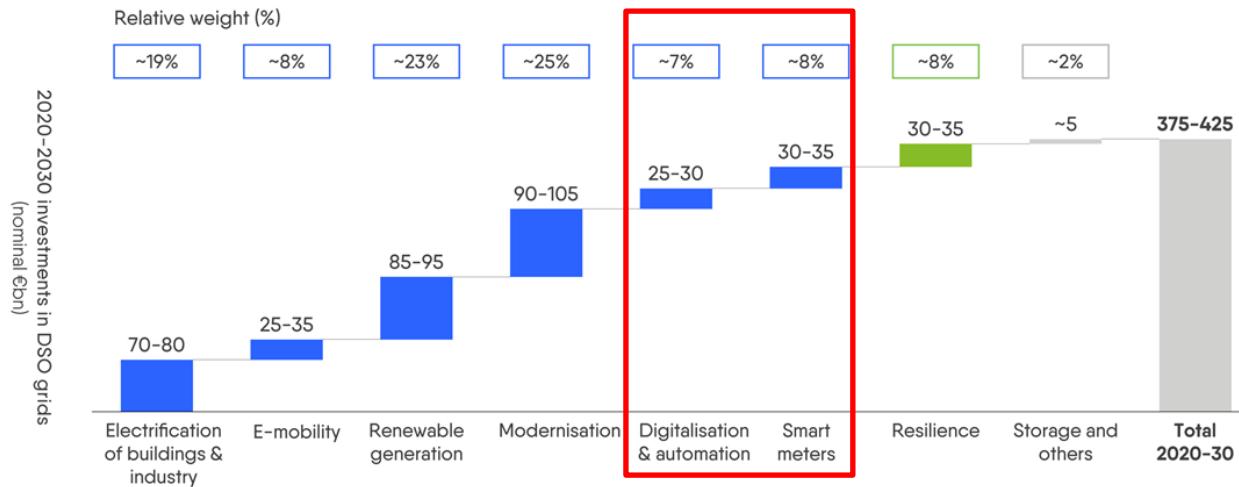






► Market perspectives

Key investment drivers: modernisation, renewables and electrification



- ¹In January 2021 Euroelectric launched a large analysis work estimating the total investment money for mitigating the green transformation
- ²Navigant Research estimates that the market size of asset management software licenses will double over the next decade from DKK 9.5 billion - to DKK 19 billion per year in 2028
- Competitors in Denmark (Sustech, Utiligize, Lithium Balance, NUUVE) focus on monitoring grid in general or other components (transformers, batteries, EVs).
- International big players (Wapice, ABB, Schneider, Siemens, Dynatrace) provide generic solutions (customization and development of new functionalities is expensive!)

¹<https://www.eurelectric.org/connecting-the-dots/>

²Utility Asset Management Systems and Analytics Navigant Research, November 2019

Projects and developments

Ongoing and new projects and initiatives at DTU

Ongoing EUDP funded project ACTION

- Smart control of grid-connected electrical drives



Ongoing InnovationFund DK funded project HEART

- Design and optimal operation of fast EV charger station



Sapere Aude (Independent Research Fund DK) funded project MAGIC

- Smart aggregation of flexible active-front-end grid-connected power electronic converters

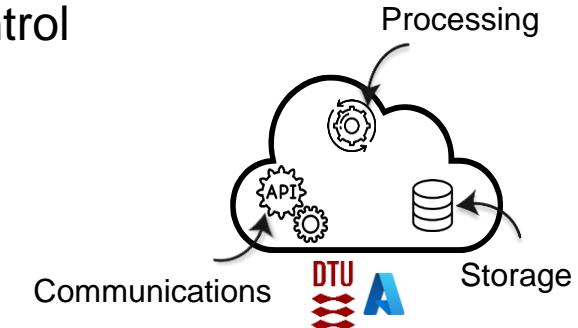


DTU Discovery grant: Development of a new DTU Cloud platform

- Integrated to PowerLabDK *Smart Converter Lab*
- Most developed algorithms for all projects are deployed via cloud control



Spin-out PHLIT ApS based on two patents and DTU Cloud

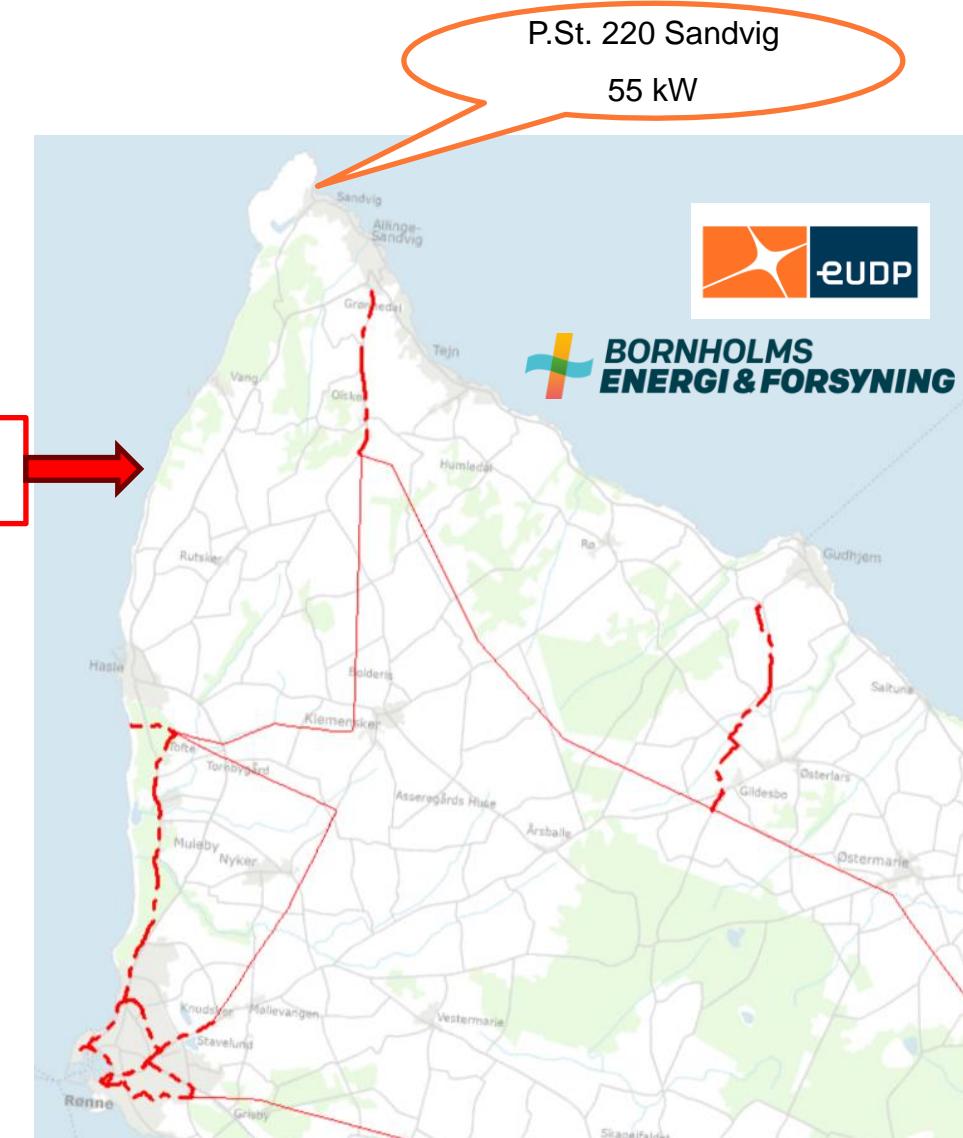


► Real world case study (Bornholm) – ACTION project

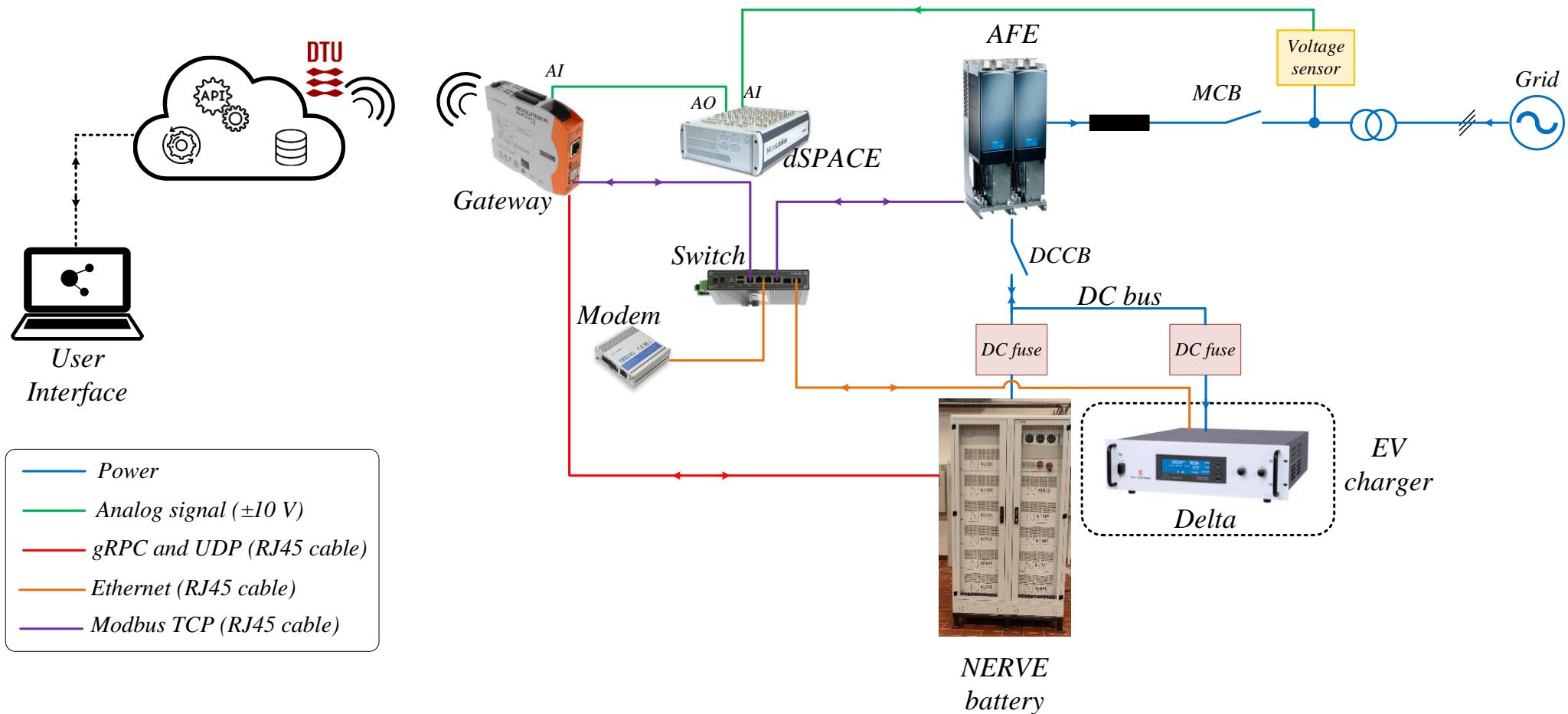
- Part of EUDP ACTION project
- Existing wastewater pump drives replaced by Danfoss drives – IoT gateway interfaced with DTU cloud platform: remote data access and controllability.
- Water flow optimized, flexibility in pump stations used as a base for the provision of remunerable grid services, online diagnostics performed.
- Good real-world case study for testing power converter asset management platform.
- **Solution is scalable – can be deployed in the same way in any converter (EV chargers, fans, compressors, electrolyzers)!**



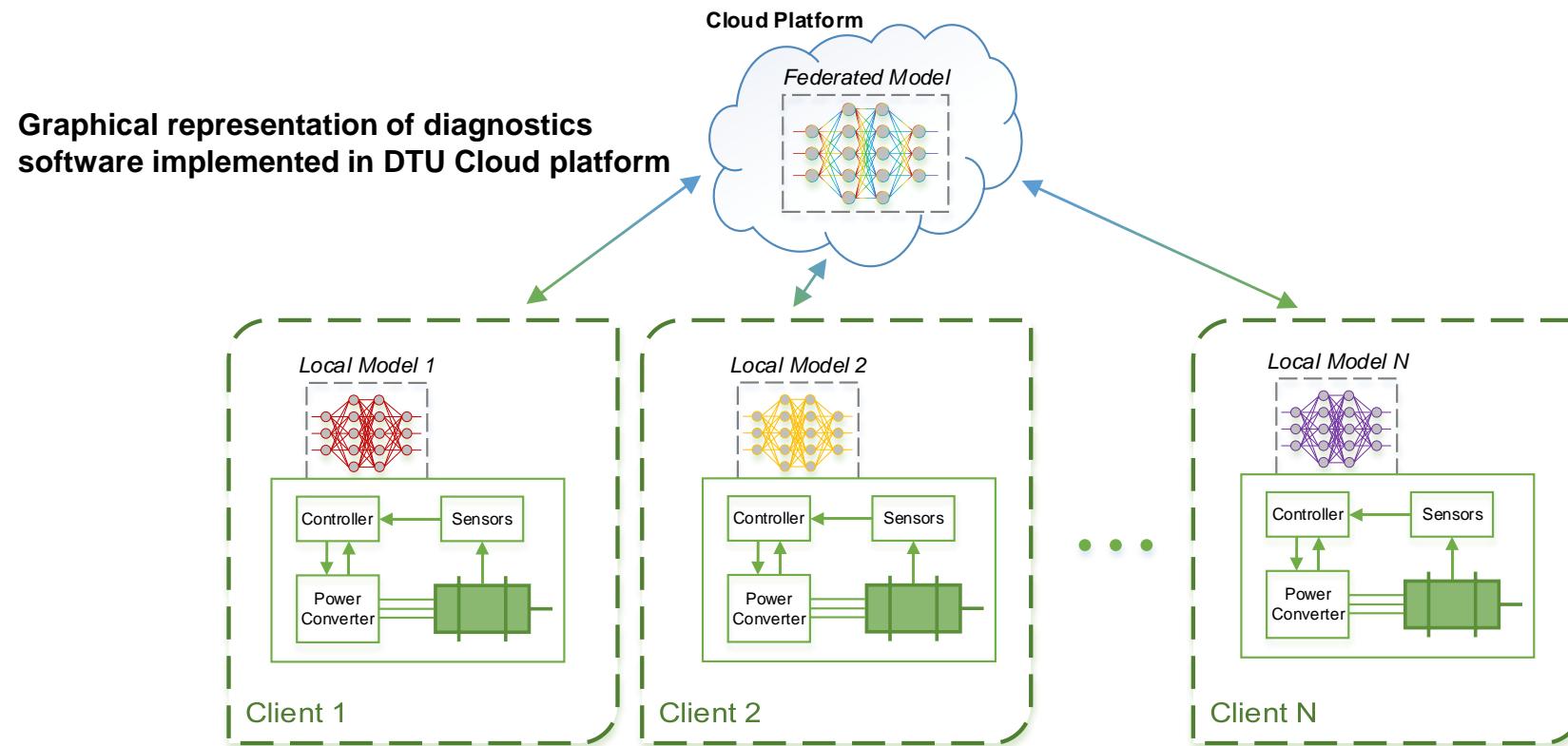
Pump station 220,
Strandvejen (Sandvig)



HEART project



Diagnostics software in a nutshell – 2 patents filed in May 2021



Objectives:

1. Converter fleet outlier detection system, with secure, lightweight communication.
2. Estimation of remaining useful lifetime of field converters.

Methods:

1. Federated learning with edge computation (transmission of models, not data).
2. Combining lab accelerated cycling tests and field data in machine learning model.

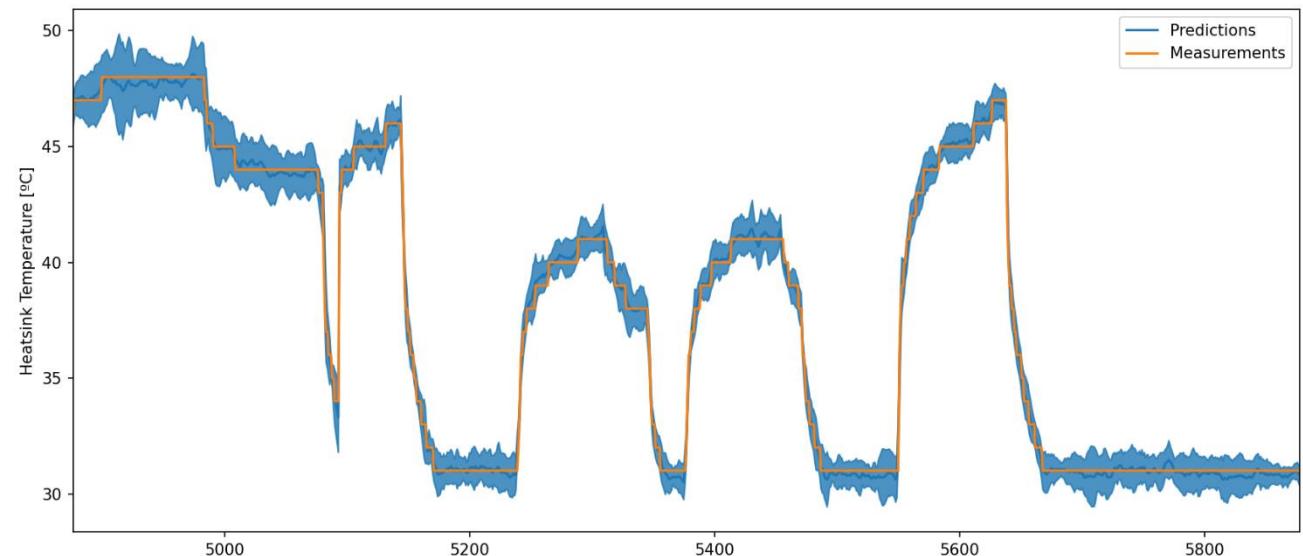
} Patents filed!

Dev 1: Condition Monitoring

1. Automate data collection with random setpoints and obtain training dataset



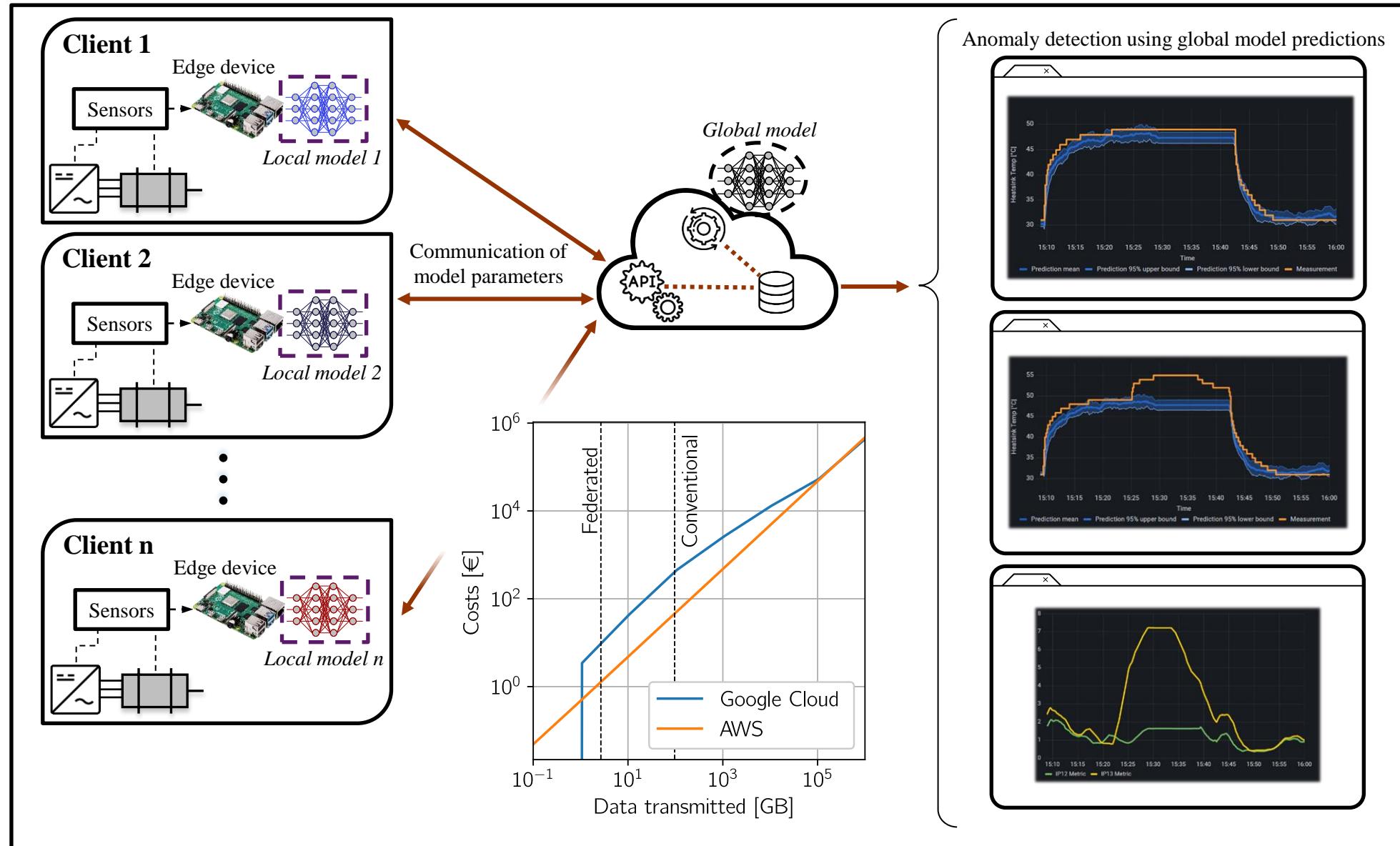
2. Training and validation neural network models

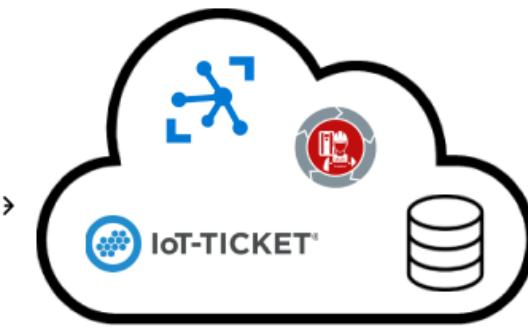
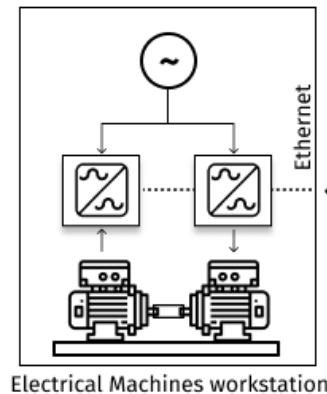


3. Deploy

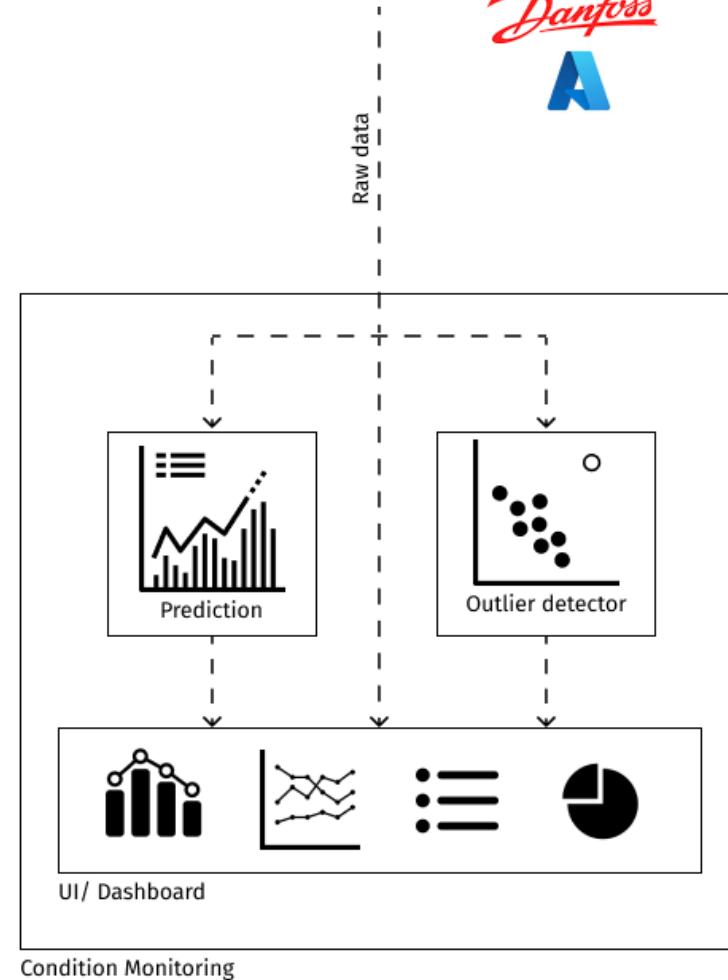


Dev 1: Converter condition monitoring



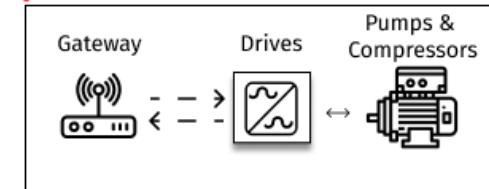


Danfoss
A

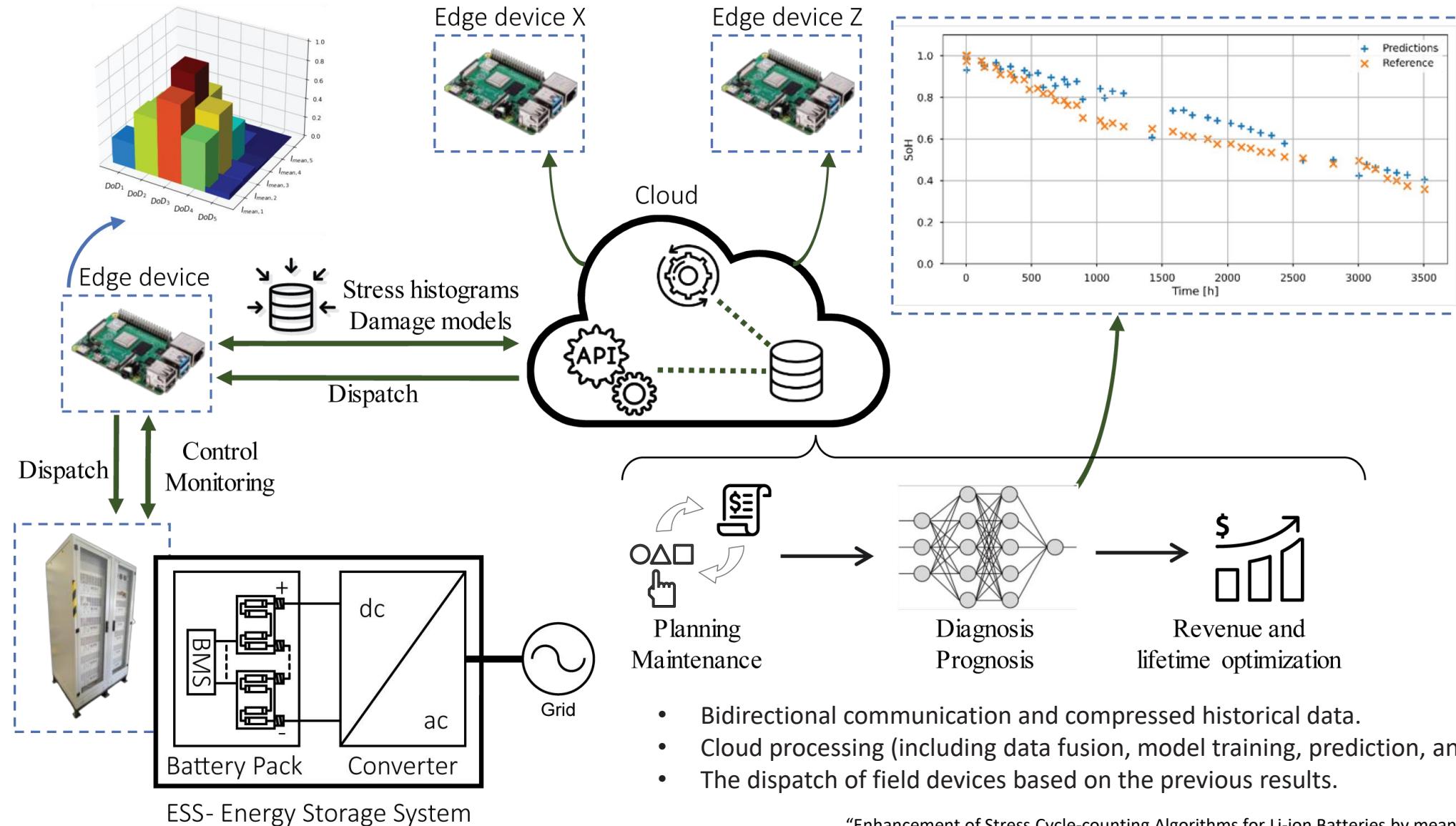


Dev 1: Condition Monitoring

Factory, water treatment plant, building



Dev 2: Battery degradation analysis & forecast



"Enhancement of Stress Cycle-counting Algorithms for Li-ion Batteries by means of Fuzzy Logic", ITEC 2022.

"A ML-based framework for online prediction of battery ageing trajectory and lifetime using histogram data", Elsevier, Journal of Power Sources.

► Generic physics-informed data-driven battery aging model

- Problem description

$$E \xrightarrow{f} \Delta C$$

E : extracted information from battery operations,
e.g., stress factors, battery capacity
 f : modeling methods
 ΔC : capacity losses

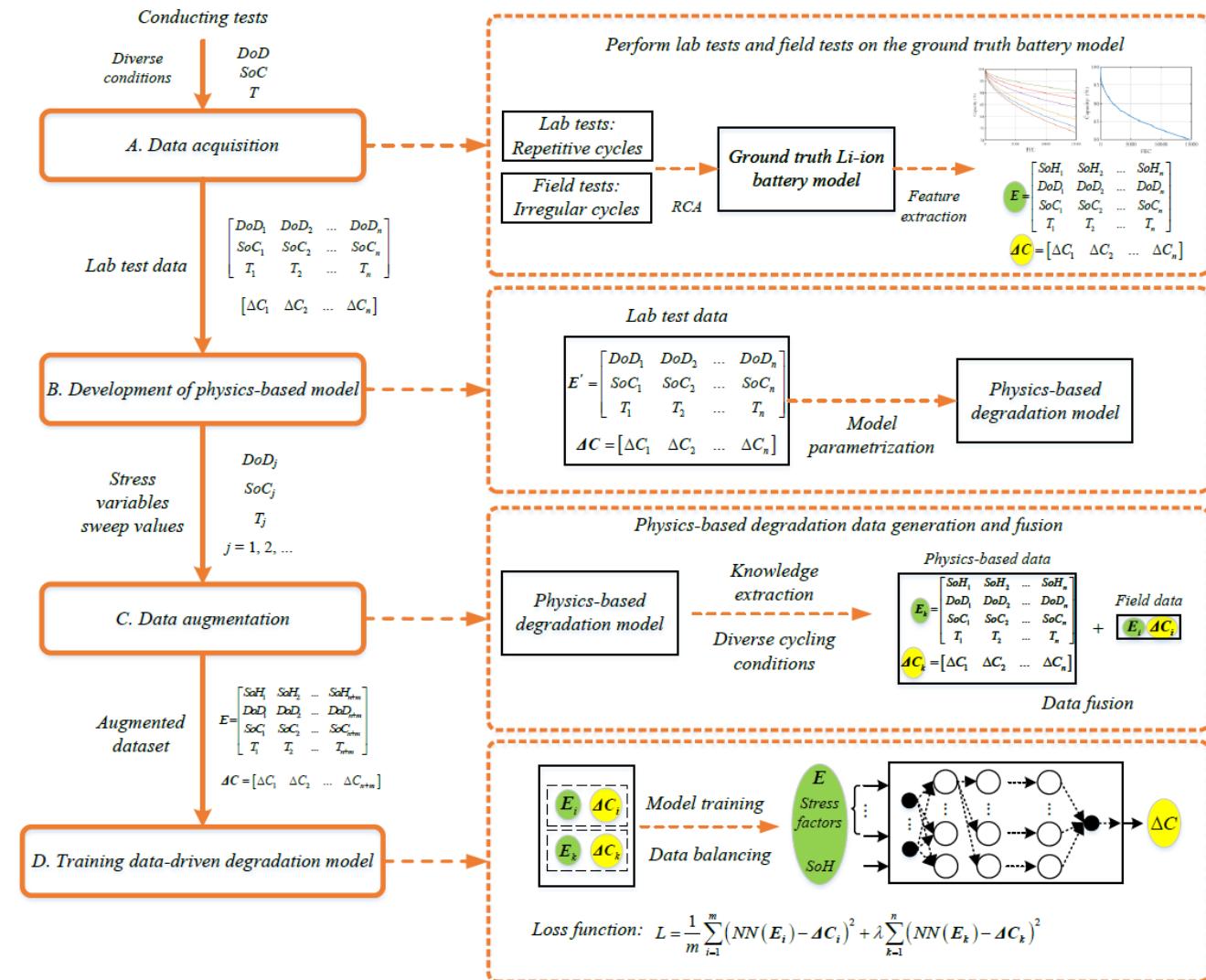
- Physics-based model

- Semi-empirical model [1]

$$L = 1 - \alpha_{sei} e^{-N\beta_{sei} f_{d,1}} - (1 - \alpha_{sei}) e^{-Nf_{d,1}}$$

- Main ideas

- Generic degradation learning method for any battery system
- Combining strengths of physics-based and data-driven degradation models
- Balancing the training with the two data sources



- Comparison among different models for a battery [2]

Indicators	Pure data-driven model	Proposed physics-informed data-driven model
MAE	0.98%	0.042%
RMSE	1.16%	0.075%
MAPE	0.459	0.138

Performance comparison for predicted loss and actual loss for all the identified cycles across degradation to end-of-life

MAE: average prediction error between predicted and actual loss

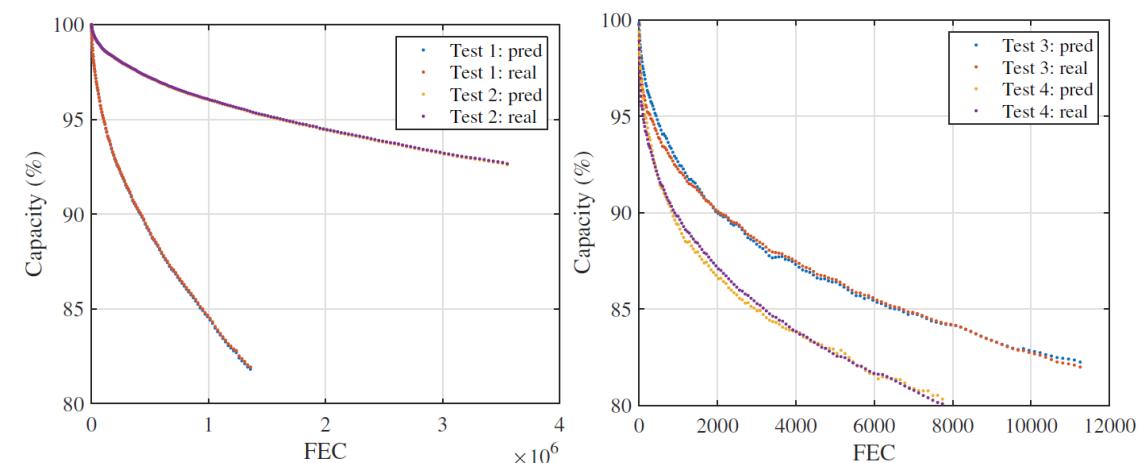
RMSE: average deviation between the predicted and actual loss

MAPE: average value between the error and the actual loss (in percentage)

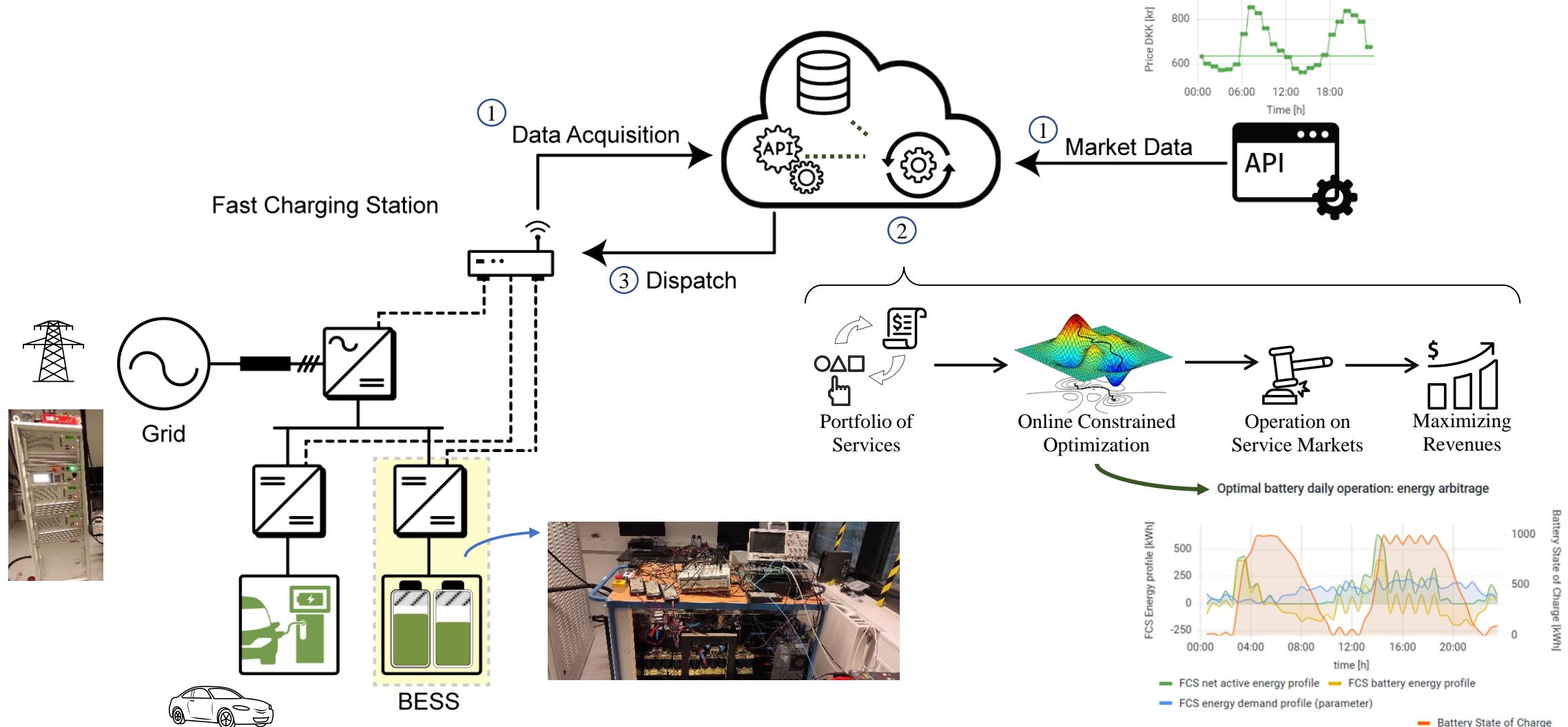
- Performance of projecting degradation process

- Dynamic test conditions
- Different battery types

Battery	Stress factors
Li(NiMnCo)O ₂ [3]	DoD
LiFePO ₄ [4]	C-rate, SoC _{avg} , DoD



Dev 3: Fast-charging station dispatch optimization



"BESS Optimal Sizing and Scheduling for Energy Arbitrage and Frequency Containment Reserve via Dual-Loop Optimization", IETEC 2022.

<https://www.energidataservice.dk/tso-electricity/FcrReservesDK2>

<https://www.coordinador.cl/desarrollo/documentos/actualizaciones-del-sistema-de-informacion-publica/api-publica-del-sip/>

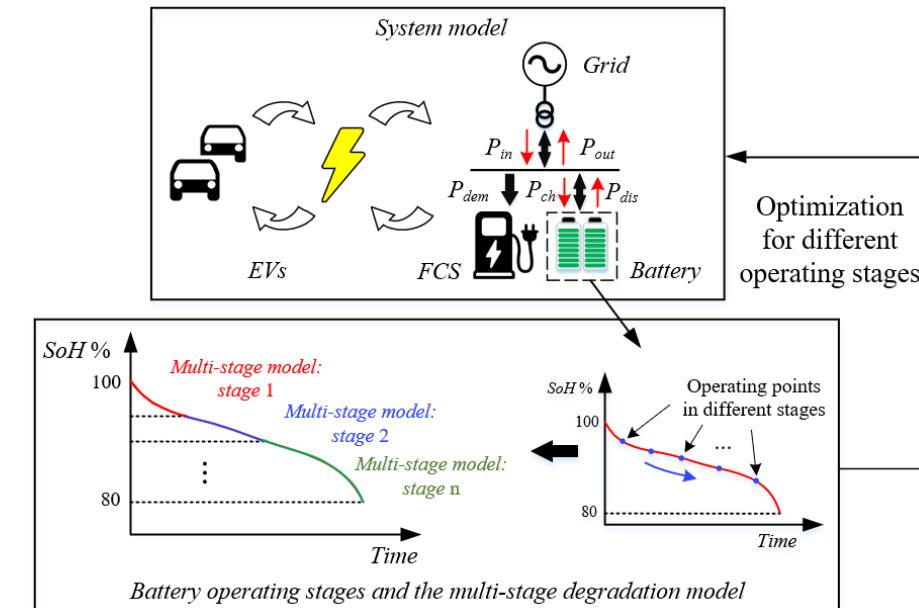
► Day-ahead scheduling with multi-stage battery degradation model

▪ Background

- Accurate formulation of **battery aging cost** for the operational planning problem is critical;
- Battery degradation process is a complex and nonlinear process, where the **degrading pattern** varies among different stages;
- Conventional methods use **single-stage models** to evaluate battery degradation for the scheduling problem across the whole operational lifetime, resulting in **suboptimal operations** and increase in **overall operation cost**.

▪ Contributions

- A novel multi-stage battery degradation modeling method;
- An adaptive scheduling framework with the multi-stage degradation model;
- Analysis regarding the number of divided stages and validations on various models.



► Implementation procedure

- **Multi-stage battery degradation modeling method**
 - Stressing factors: C-rate, DoD, etc.;
 - Segmentation of the aging experimental data^[1] for different degradation stages;
 - Model parameterization for different aging stages with the experimental data.

- **Scheduling model**

- Objective function

$$J_t = \min_{P_t^{ch}, P_t^{dis}} \sum_{t=1}^T (P_t^{in} - P_t^{out}) \cdot p_t + \lambda_k \cdot C_t$$

- Constraints

- Energy balance:

$$P_t^{in} - P_t^{out} = P_t^{ch} - P_t^{dis} + P_{dem}$$

- Battery operation:

$$SoC_t = SoC_{t-1} + \frac{1}{C_{bat}} \left(\eta_{ch} P_t^{ch} - \frac{P_t^{dis}}{\eta_{dis}} \right),$$

$$SoC_{t=T} = SoC_{end},$$

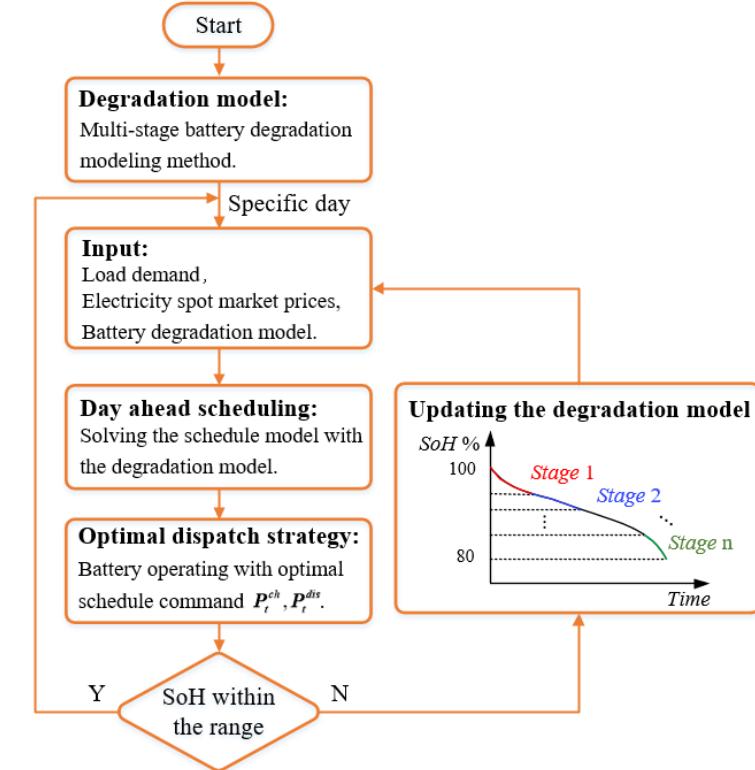
$$SoC_{\min} \leq SoC_t \leq SoC_{\max},$$

- Power limits

- Formulation of battery aging cost

- Battery degradation model^[2]

$$Q_{loss} = \sum_{t=1}^T \frac{(\Delta DoD_t)^{\frac{1}{\alpha}} \cdot (2I_t^{ch/dis})^{\frac{1}{\alpha}} \cdot \exp\left[-\varphi\left(\frac{1}{T_a} - \frac{1}{25}\right)\right]}{N_{cref}}$$



Nomenclature:

P_t^{ch}, P_t^{dis} : dispatch command; P_{dem} : load demand;

P_t^{in}, P_t^{out} : energy flow from/to grid to/from FCS;

p_t : electricity spot market price,

λ_k : replacement cost, C_t : battery capacity loss;

Q_{loss} : formulation of battery degradation;

SoC_t : battery state-of-charge; DoD_t : depth-of-discharge

C_{bat} : nominal battery capacity.

- Comparison

- Multi-stage modeling on a cycle life model (three stages)

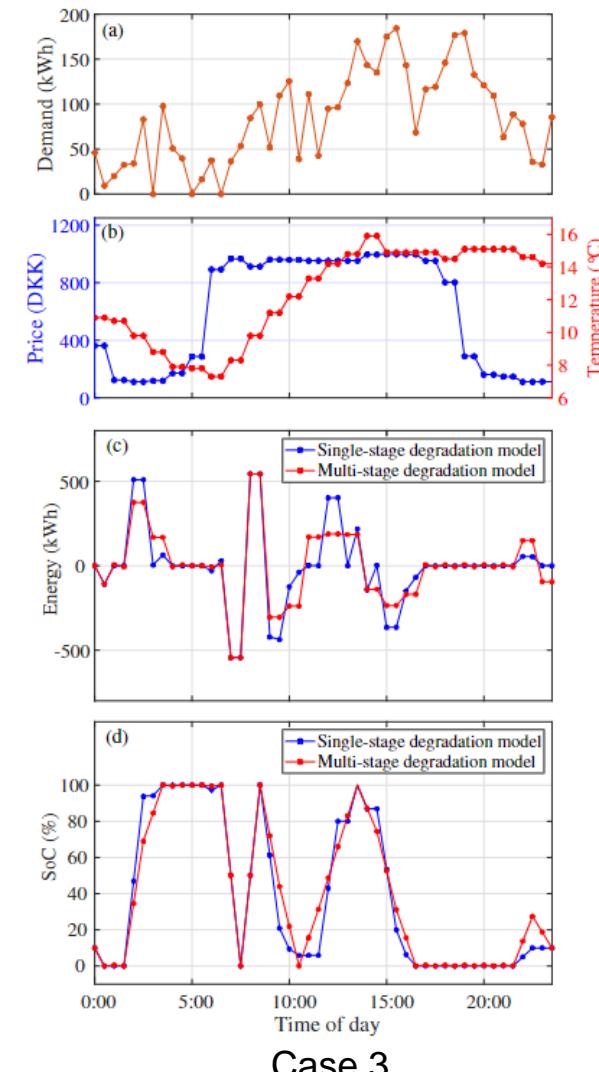
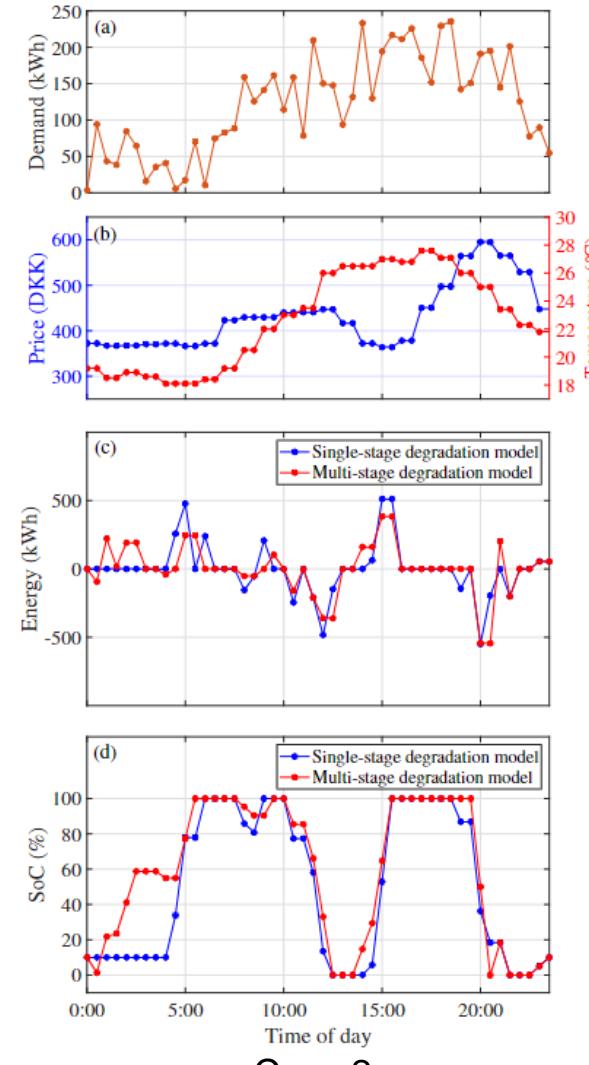
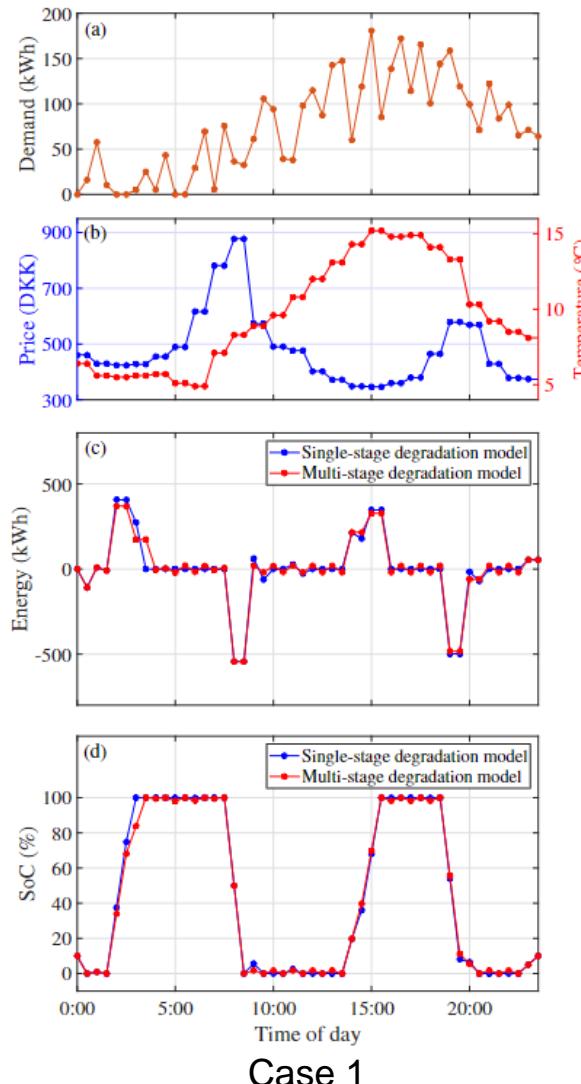
Tests/RMSE	Stages	Single-stage model	Multi-stage model
Test 1	Stage 1	0.78%	0.50%
	Stage 2	2.21%	0.42%
	Stage3	3.15%	1.10%
Test 2	Stage 1	1.00%	0.78%
	Stage 2	2.37%	0.75%
	Stage3	2.86%	1.28%

- Day-ahead scheduling for three example days (representing different stages)

Cases	Case 1		Case 2		Case 3	
	Single-stage model	Multi-stage model	Single-stage model	Multi-stage model	Single-stage model	Multi-stage model
Battery degradation (%)	0.0327	0.0290	0.0594	0.0458	0.0505	0.0222
Energy arbitrage revenue (DKK)	1213.12	1212.42	685.75	697.48	1420.74	1419.08
Operation cost (DKK)	459.45	453.94	2032.24	1997.14	1452.07	1404.42

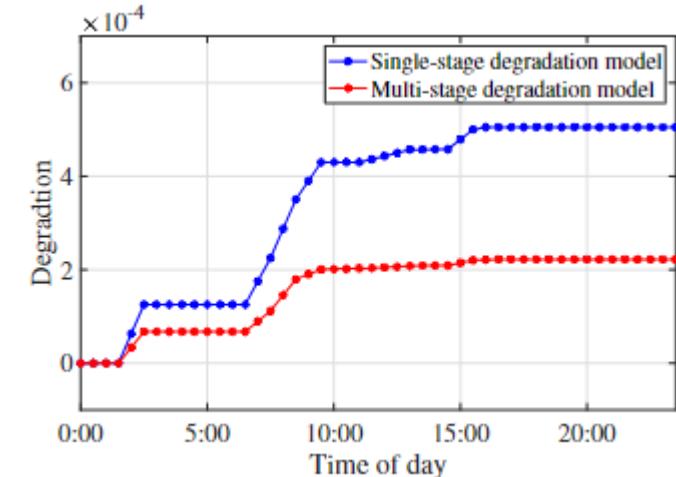
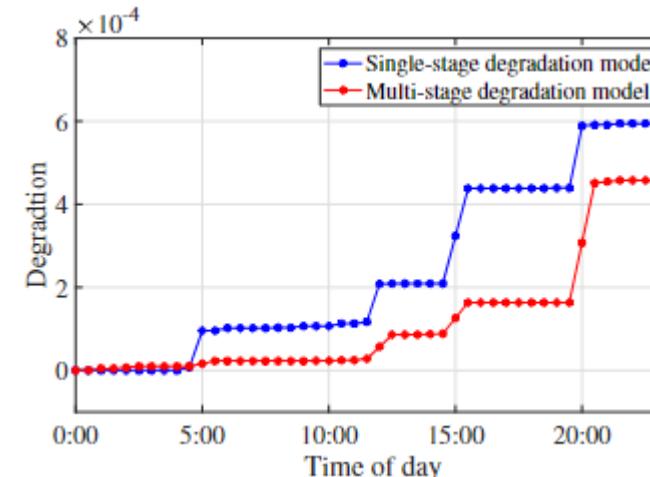
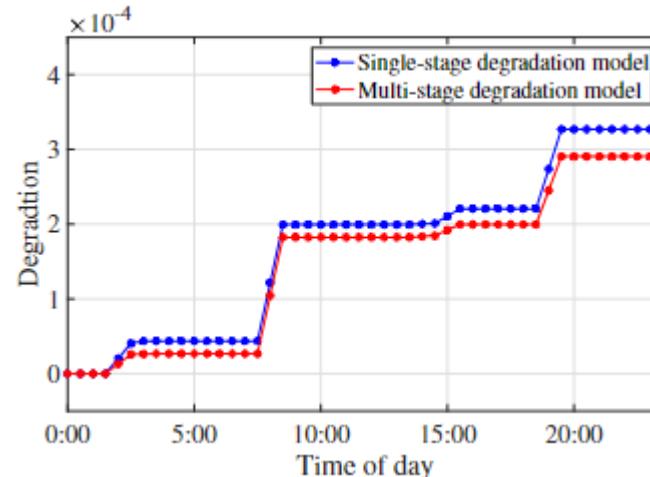
► Case study

- Scheduling results

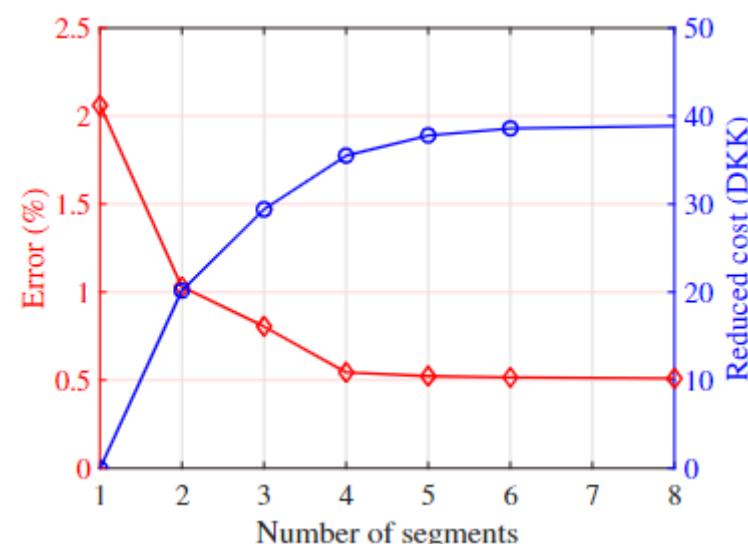


► Case study

- Accumulative battery degradation across a day

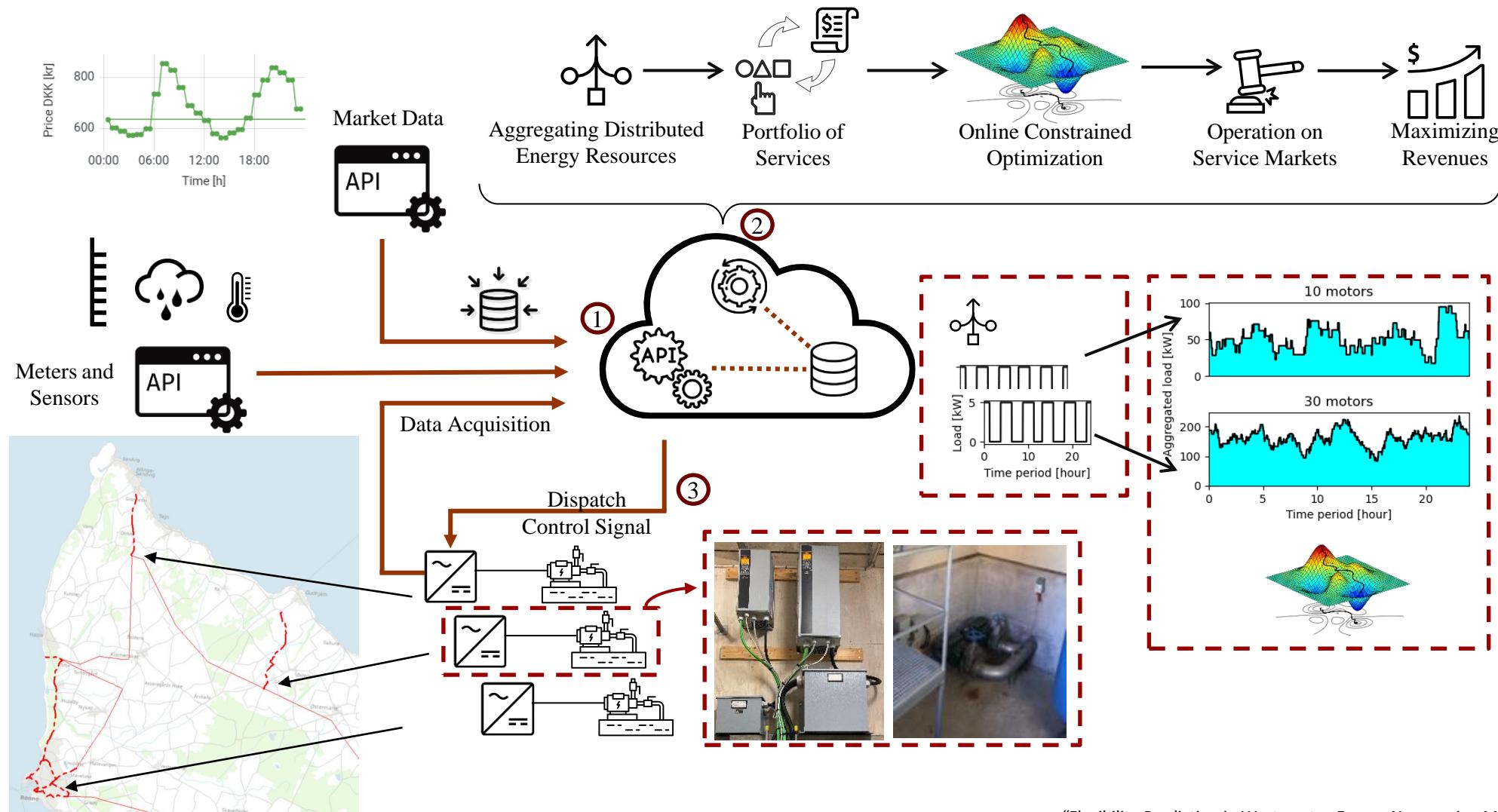


- Sensitive analysis regarding the number of divided stages



Blue line: reduced operation cost
(compared with the basic single-stage model)
Red line: model accuracy for validation dataset
(RMSE in percentage)

Dev 4: Distributed wastewater pumping system coordination



"Flexibility Prediction in Wastewater-Energy Nexus using Machine Learning", IECON 2022.

FlexGate® solution

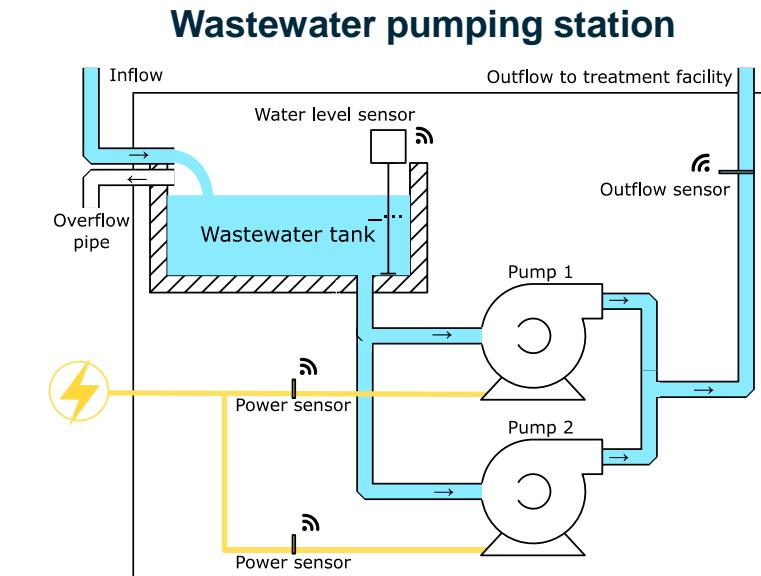
- **Transforms wastewater tanks into virtual batteries** by modifying the outflow pumping rate:

- ✓ Before expected rain, tank is emptied to give more buffer and prevent (excessive) overflows
- ✓ Optimal pumping rate enforced whenever water in the tank is at moderate level
- ✓ Pumping reduced or increased from the baseline level to support the grid (in coordination with other flexible assets)

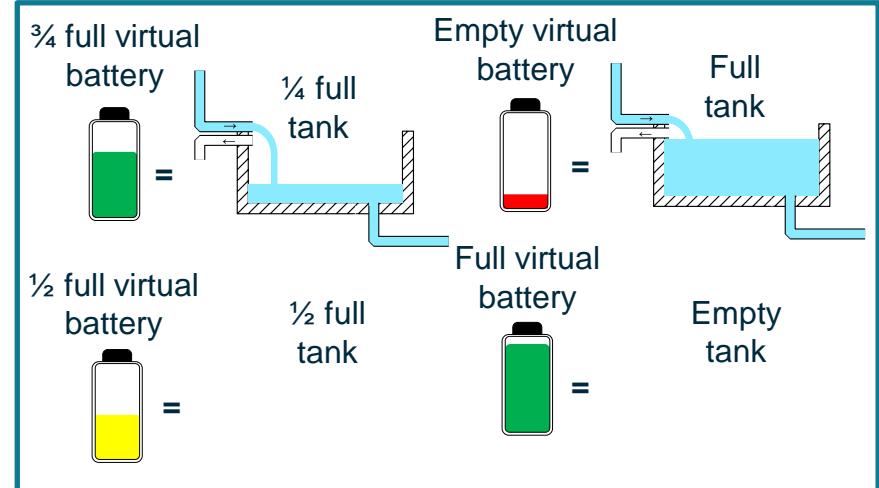
- **Virtual battery characteristics:**

- Tank capacity does not degrade
- No use of critical raw materials or footprint
- Lossless round trip charge cycle (because overall volume is pumped anyway)
- Provides short-term storage (up to 15 min)

**Solution demonstrated in a real-world wastewater pumping station
(Rønne, Denmark)**

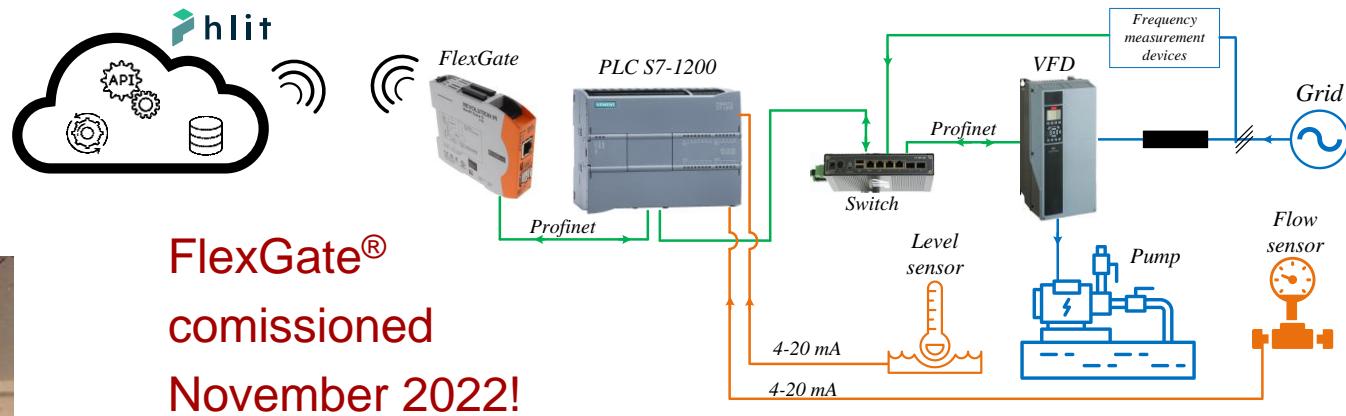


Distributed fleet of virtual batteries



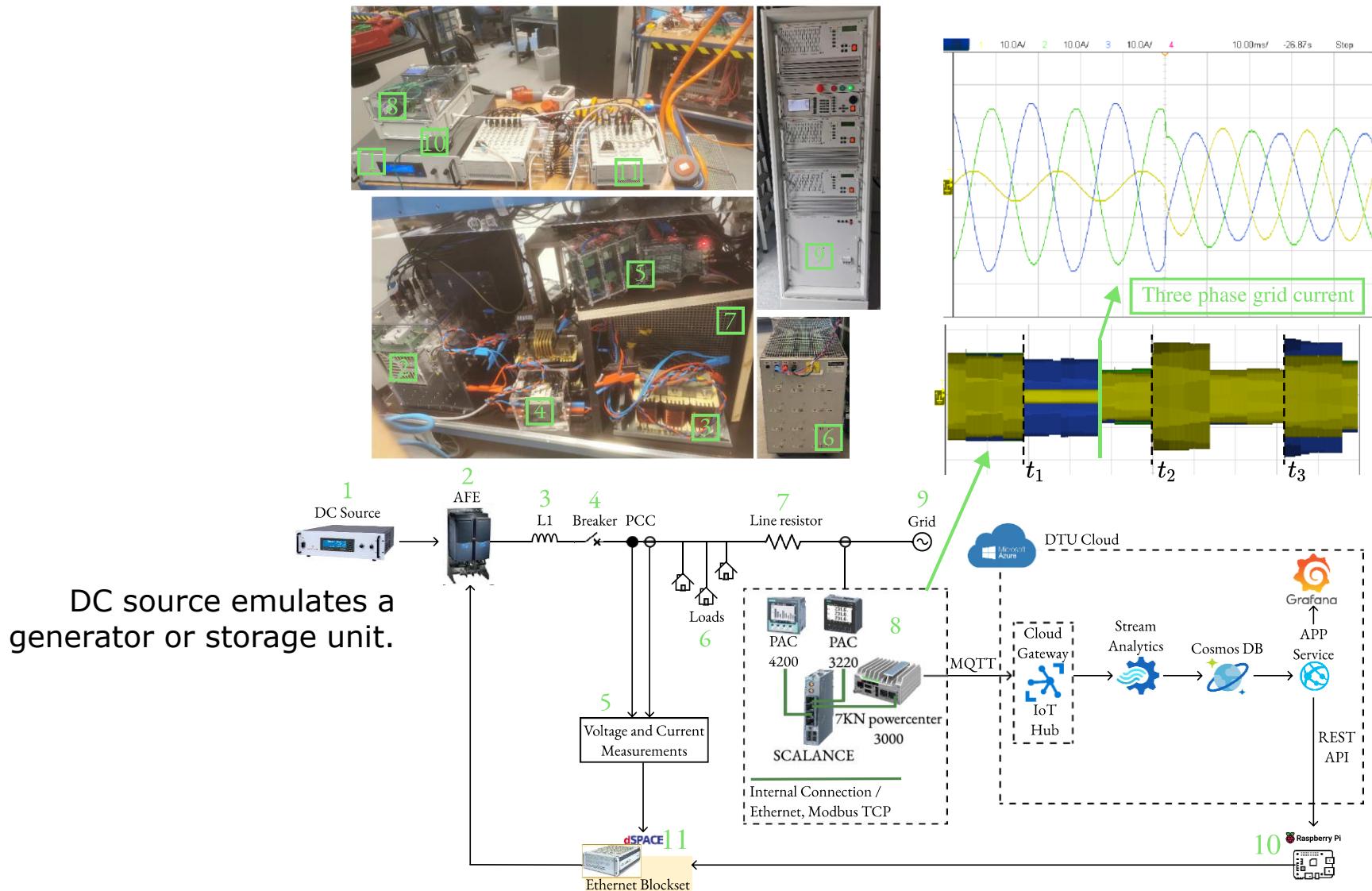
Bornholm's Spildevand A/S: pilot project

FlexGate installed at 3 other test sites, more trial projects planned



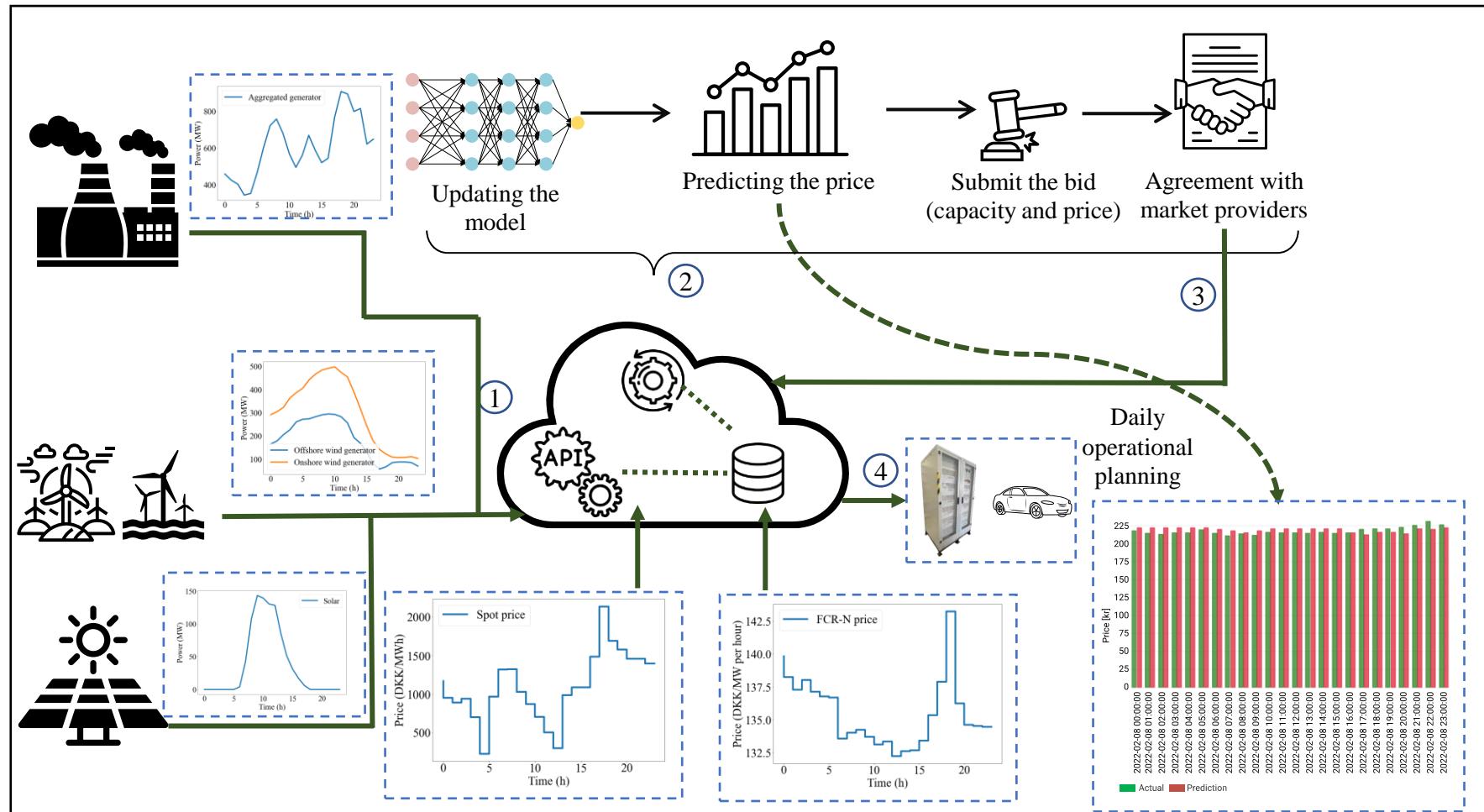
- **Data collected from the PLC with 1 sec update rate**
 - Water level, outflow, pump speeds, pump powers
 - Data processing and controller synthesis automation fully streamlined
- **5 kW / 5 kWh virtual battery unlocked:**
 - Up to 10% efficiency improvement enabled
 - Aggregation with other flexible assets for grid service provision enabled
 - Performance validated with grid operator

Dev 5: Voltage imbalance compensation

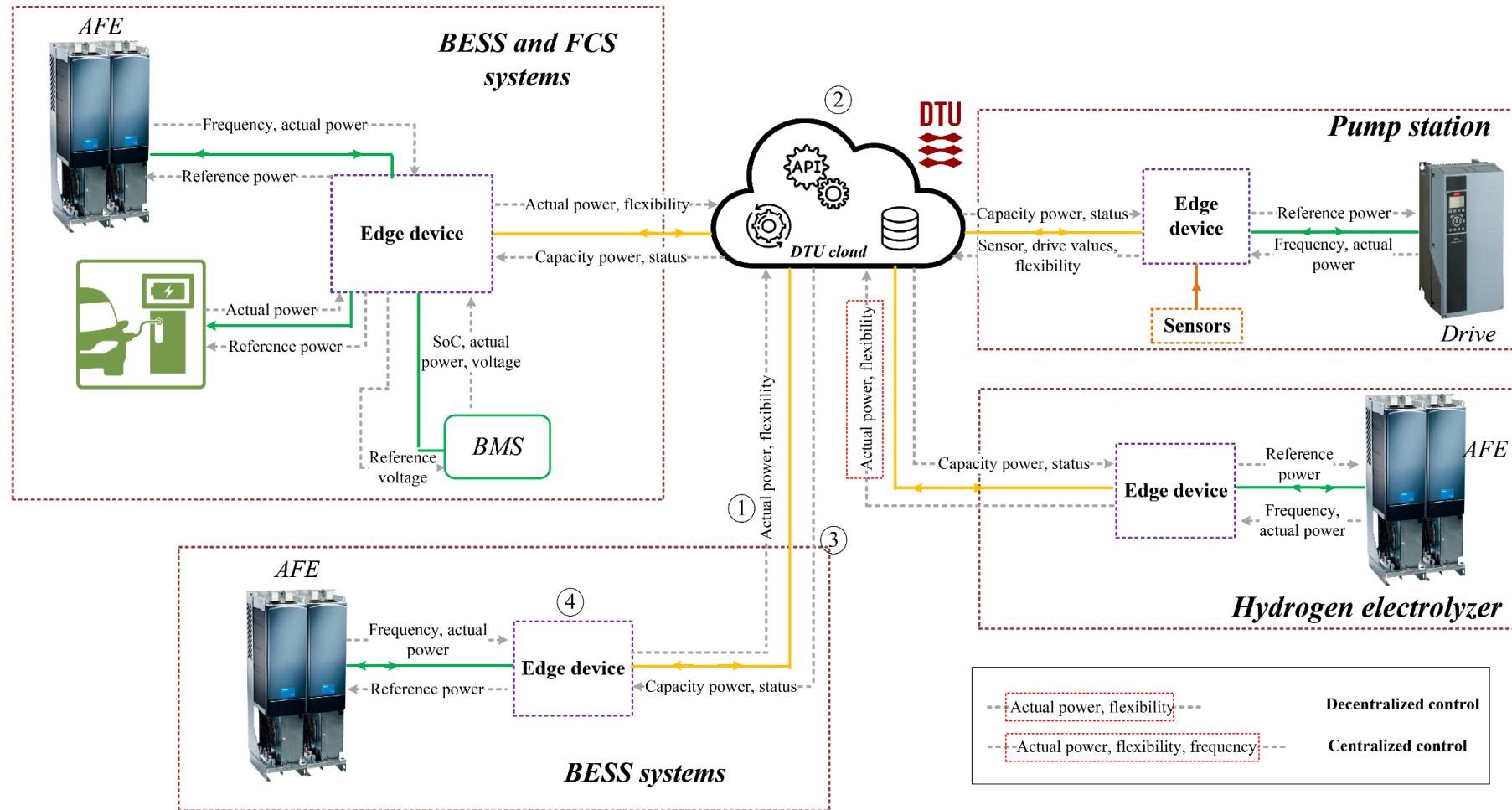


- Load imbalances are created at t_1 , t_2 and t_3 .
- GMU registers currents, phase-shifts, and power factor.
- IoT Hub is used to send data every 15s.
- Rpi used as intermediate with Cloud and dSPACE.
- Negative sequence reference updates the controller every 30s.
- The unbalanced voltage is compensated by injecting the negative sequence of the grid current through the converter.

Dev 6: Frequency regulation Market Bidding



Dev 7: The operation of Virtual Power Plants



Simulation:

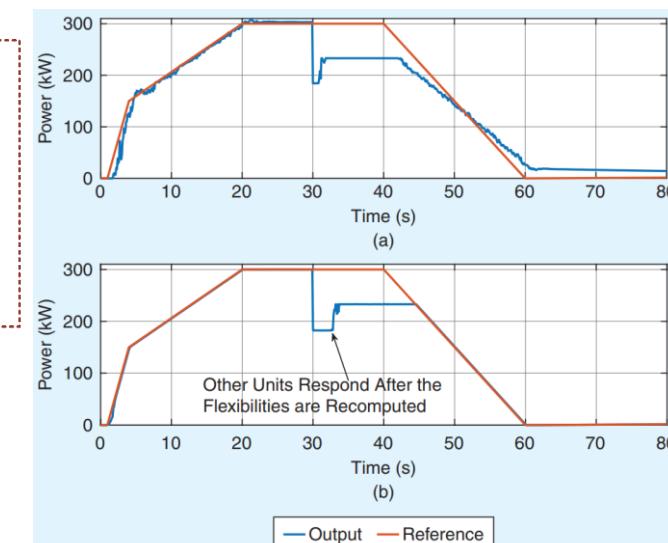
The total agreed power delivery with the TSO is 300kW.

The time step of updating the available flexibilities is 2s.

5 units of $P=\{50,100,33,50,150\}$ kW

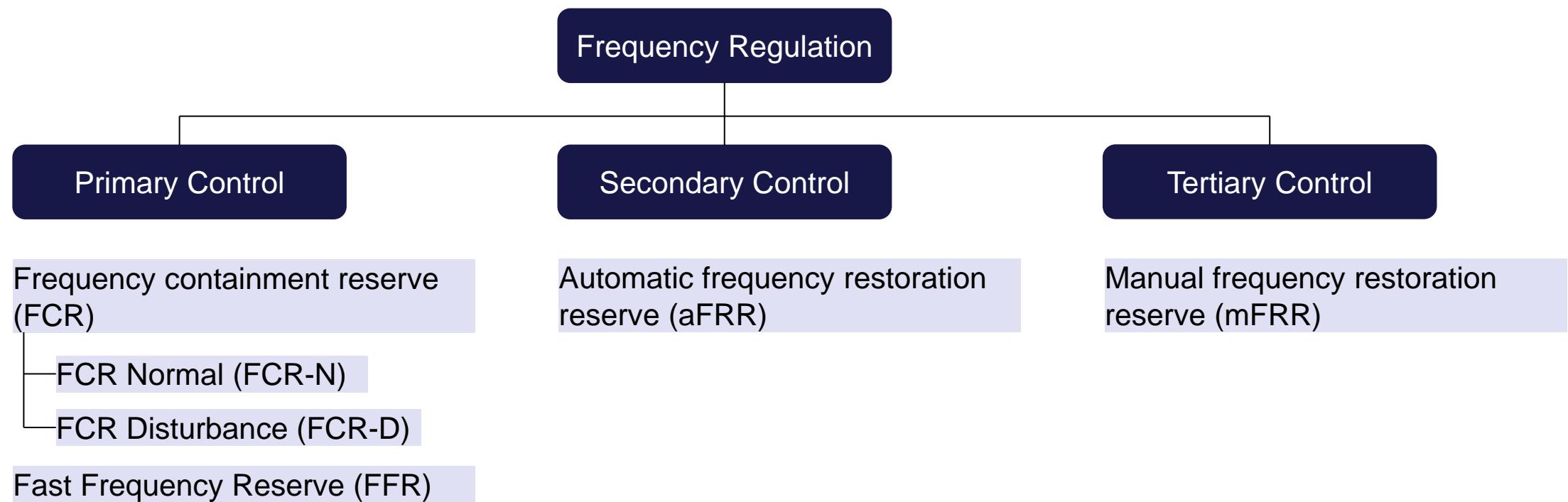
FCR-D on each unit.

At $t=30$, unit 5 experiences malfunction.

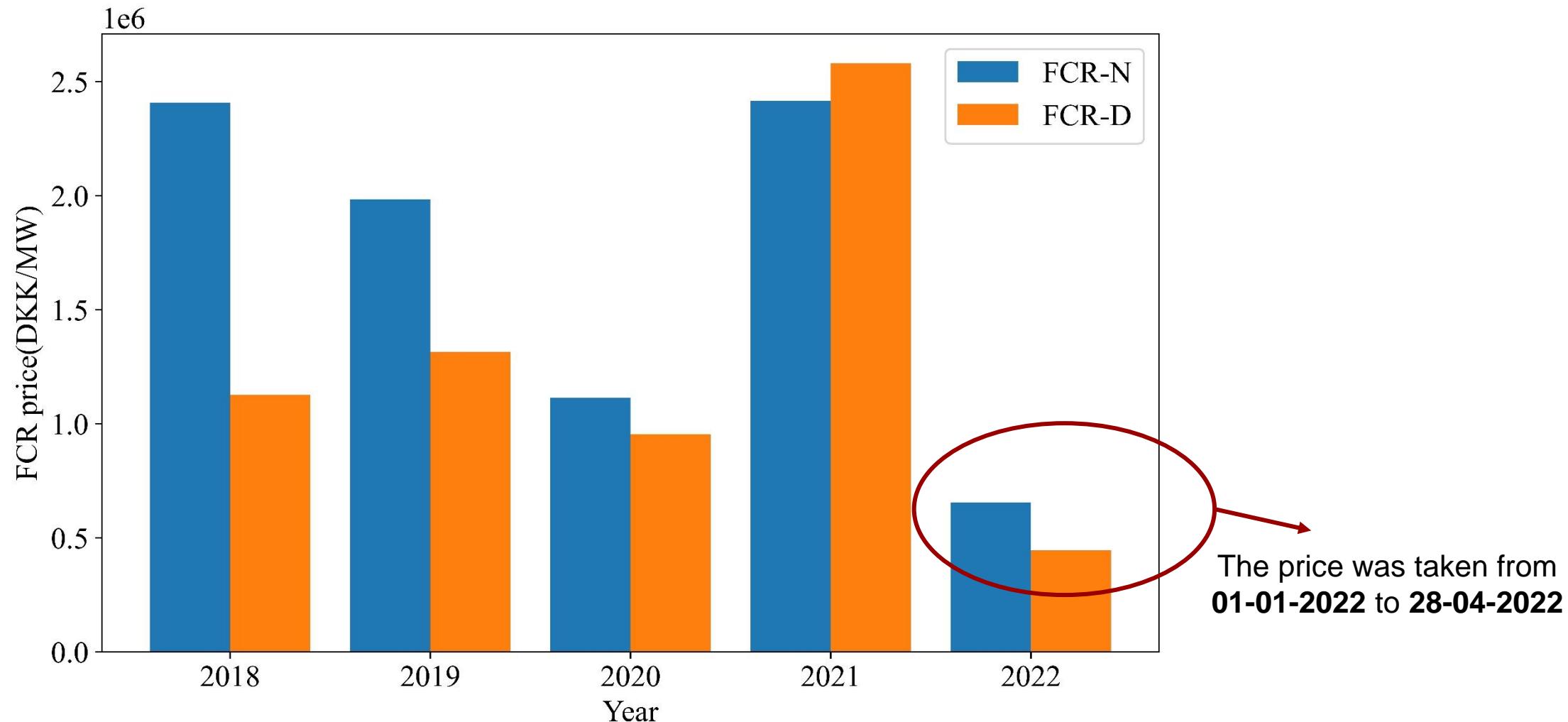


Thanks for your attention!

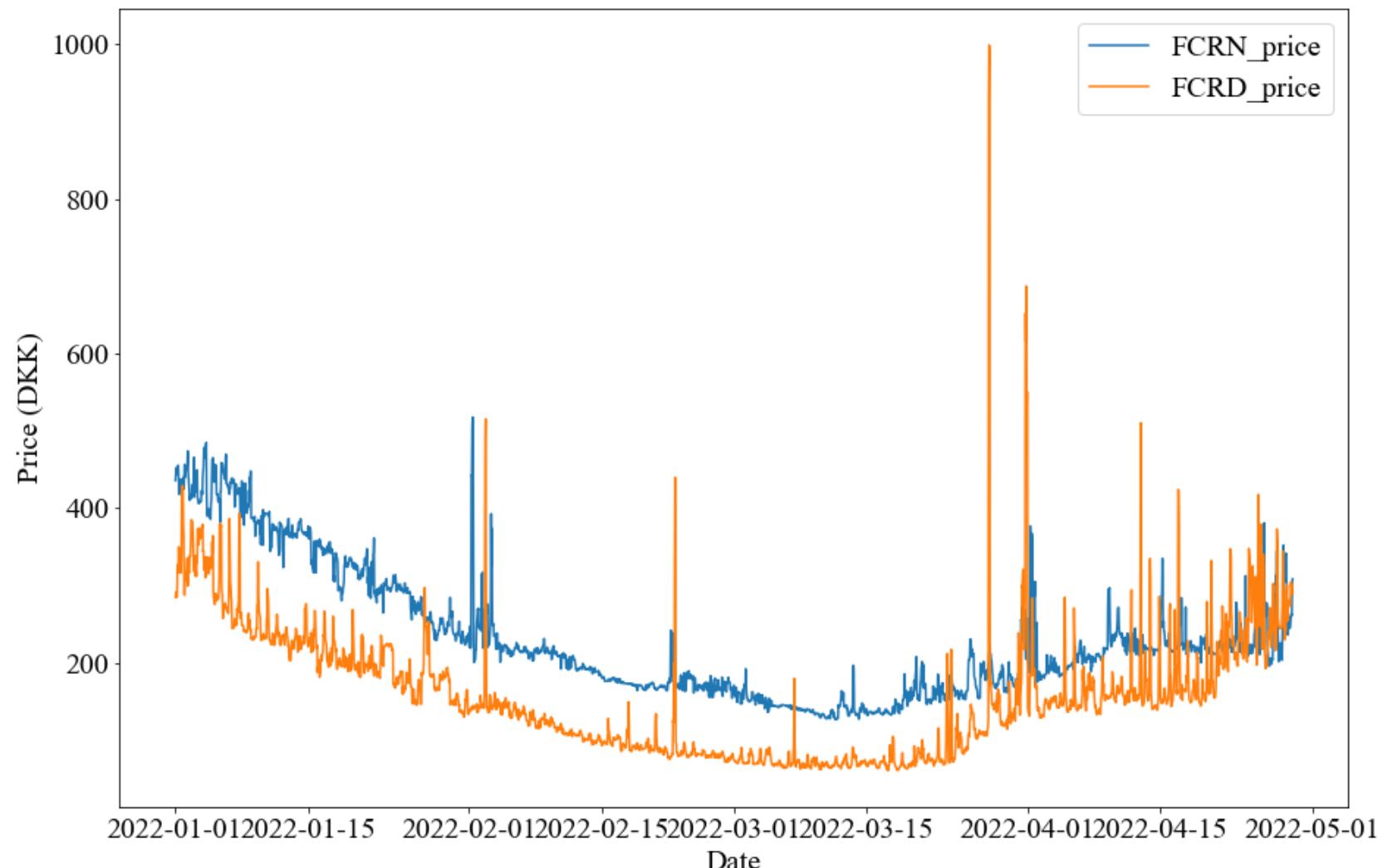
Frequency Reserve Market



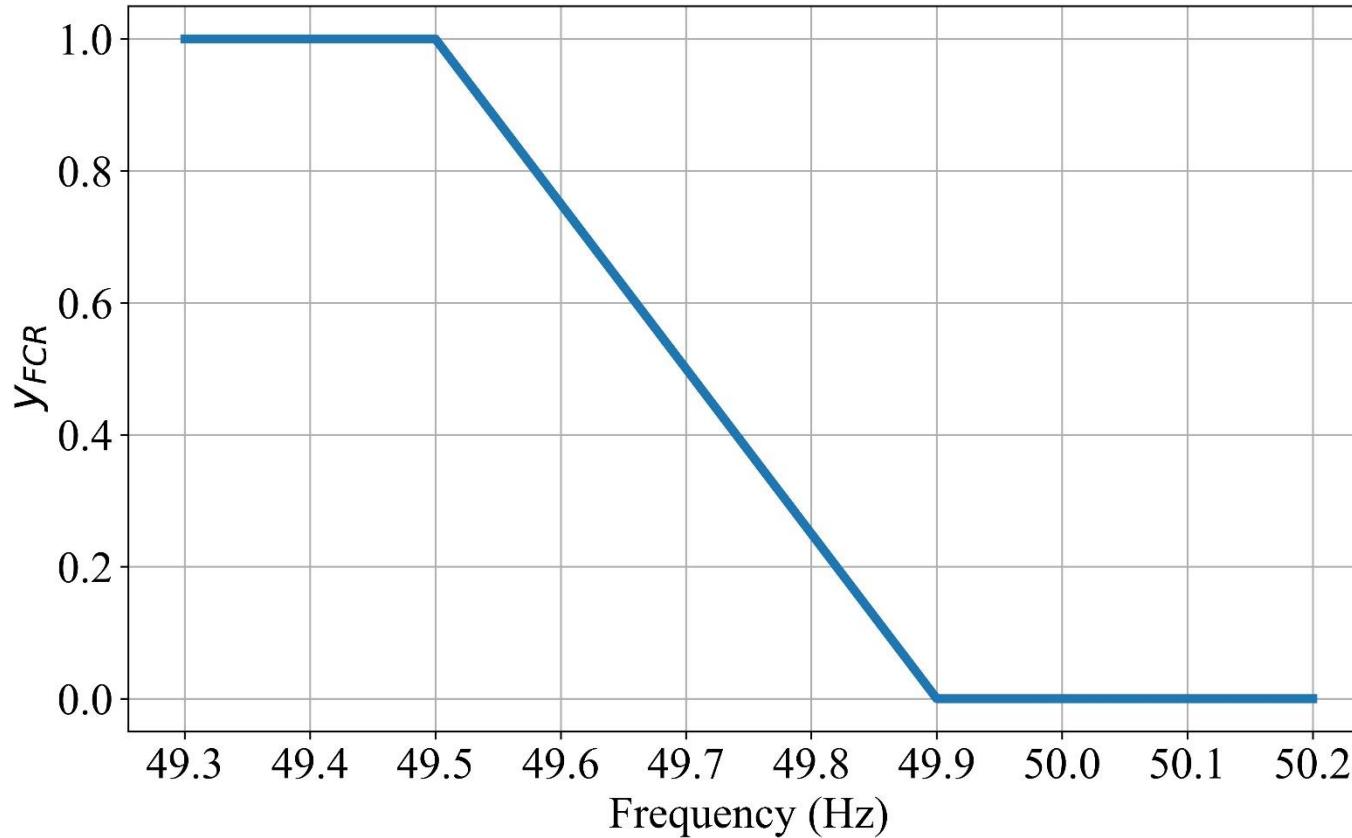
FCR price in DK2



FCR price in DK2 (2022)



Frequency Containment Reserve Disturbance (FCR-D)



- Upward regulation, activated when the frequency $< 49.9 \text{ Hz}$
- The capacity given is a function of frequency, formulated as

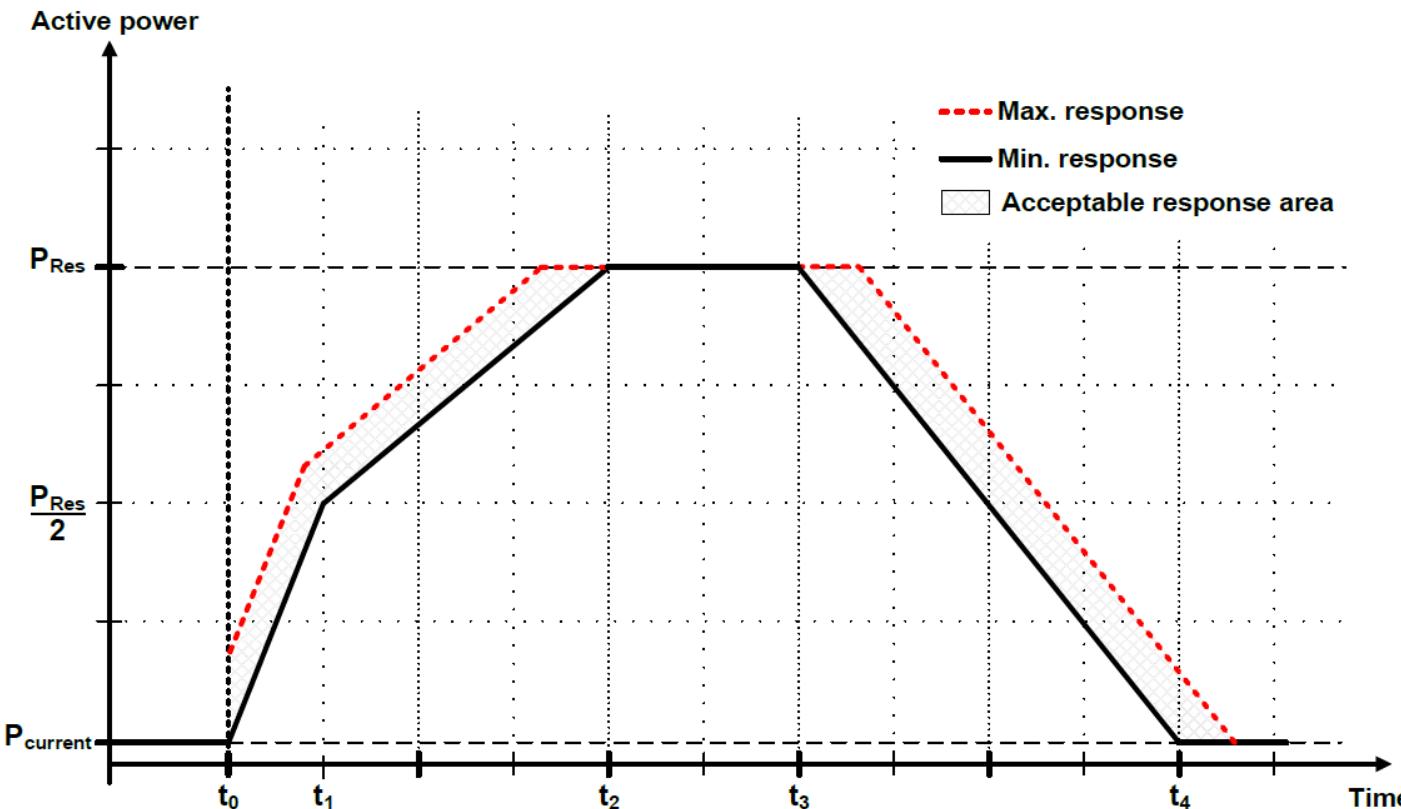
$$y_{FCR} = \begin{cases} 1 & f < 49.5\text{Hz} \\ \frac{49.9 - f}{0.4} & 49.5 \leq f \leq 49.9 \\ 0 & f > 49.9\text{Hz} \end{cases}$$

$$P_{FCR_D} = y_{FCR} P_{cap}$$

Measurement requirements:

- Minimum measurement accuracy is 10mHz
- Minimum measurement sensitivity is 10mHz
- Minimum resolution (time step) is 1 second

Frequency Containment Reserve Disturbance (FCR-D)



Response and Response Time:

- 50% of capacity within 5 seconds
- The remaining 50% capacity within an additional 25 seconds

Re-establishment period:

- If full capacity has been delivered for minimum 15 mins, the units are allowed to re-establish for maximum 15 mins.

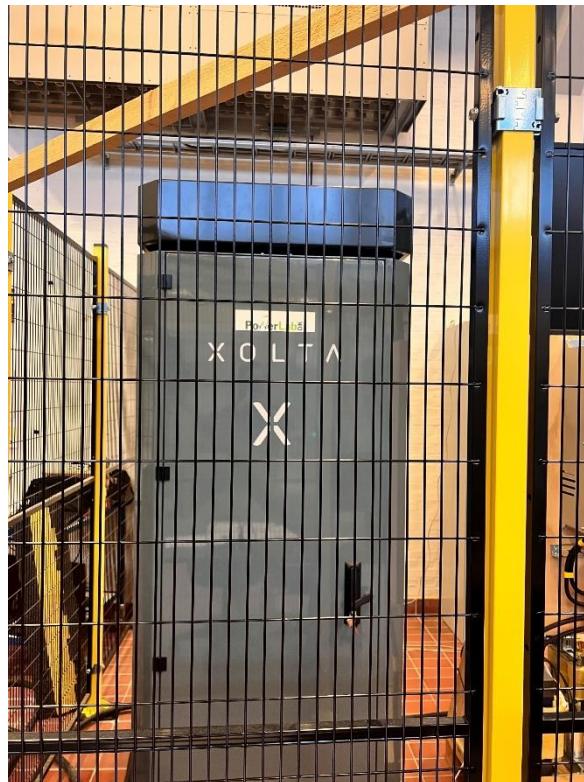
$$R = \frac{1}{15 \cdot 60} \sum_{t=1}^{\min(n, 3600)} y_t \quad \text{If } R = 1, \text{ then we allow to re-establish for maximum 15 mins, then } R=0$$

Minimum bid size:

- 0.3 MW

Frequency Containment Reserve Disturbance (FCR-D)

Potential assets:



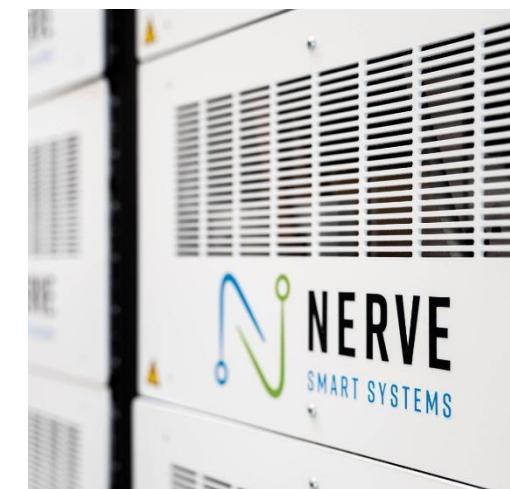
79 kW



33 kW



30 kW



30 kW

Frequency Containment Reserve Disturbance (FCR-D)

