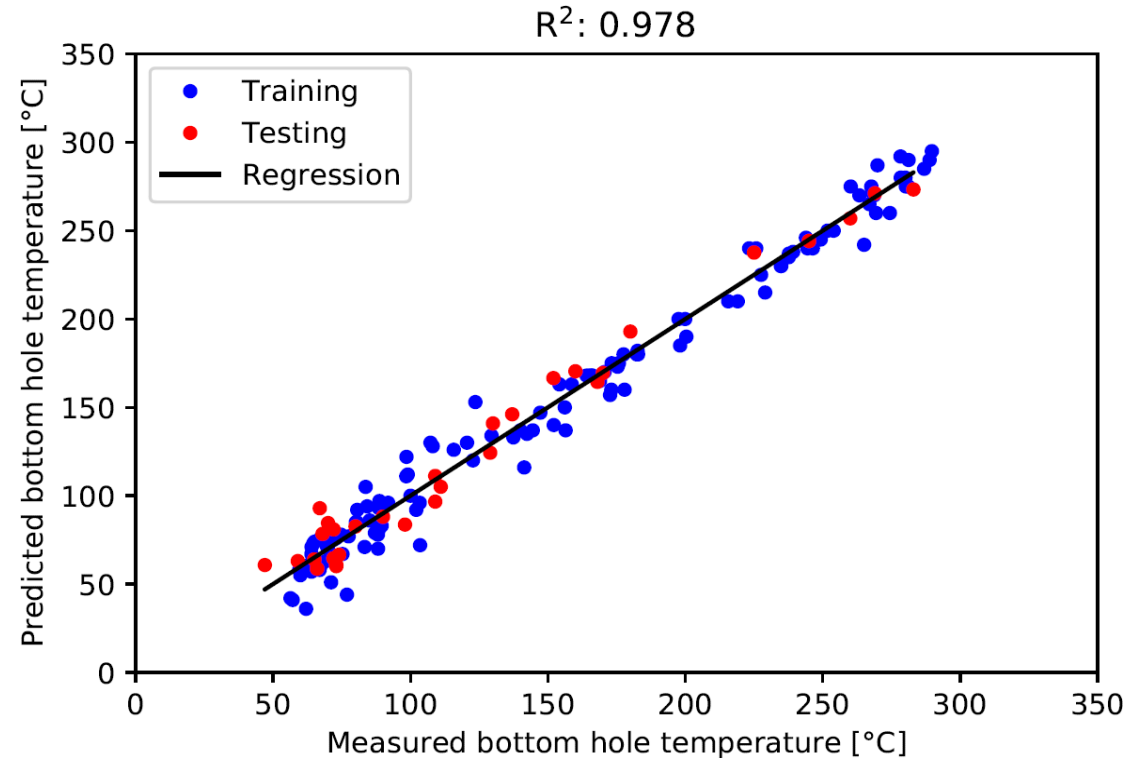


# Increasing the Efficiency of Geothermal Power Plants by Coupling with Artificial Intelligence

Michael Trumpp, Lars Yström, Valentin Goldberg, Florian Eichinger, Johannes Amtmann, Roman Lutz, Daniel Winter, Joachim Koschikowski, Thomas Kohl, Fabian Nitschke

# Motivation - Machine learning for exploration

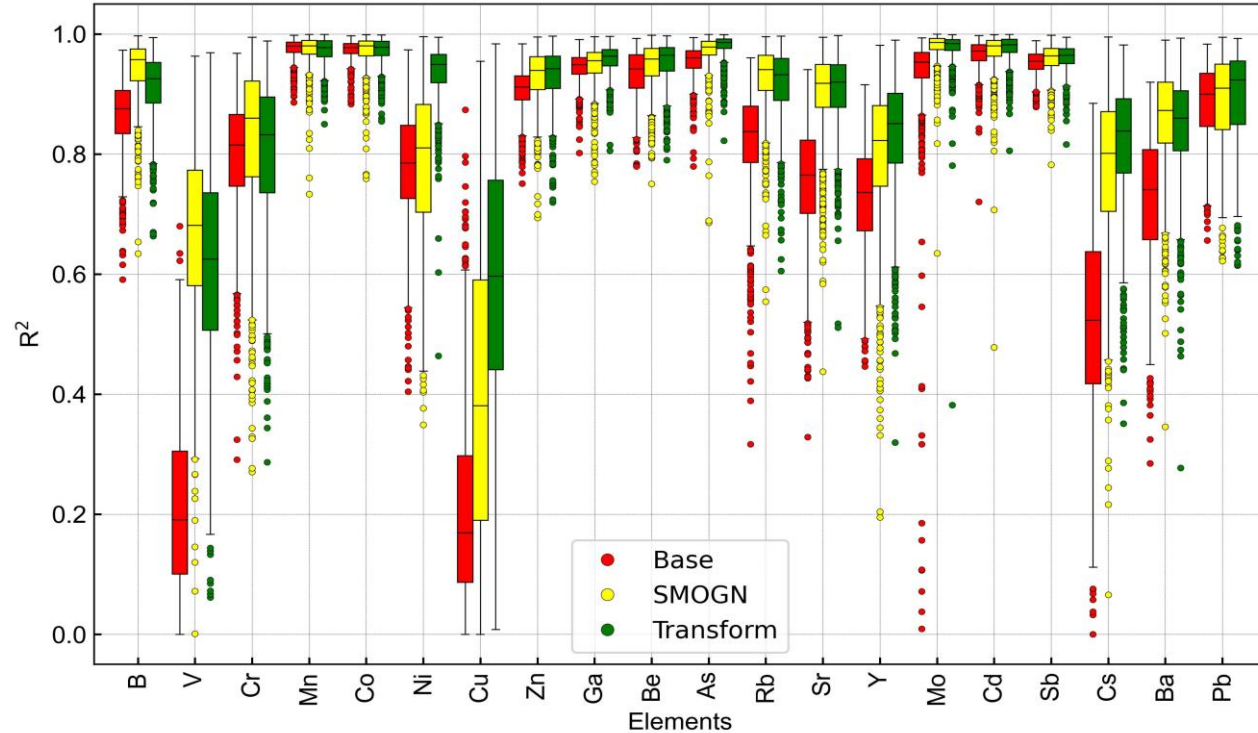
- Example of reservoir temperature estimation
  - Based on geochemical fluid parameters
  - Hydrochemical composition used for multi component geothermometer
  - Proofed that small data sets of 80 entries are sufficient



YSTROEM, 2023

# Motivation - Machine learning for exploration

- Development from a single element prediction (Li) to a multi prediction tool
- Prediction of geothermal fluid composition with focus on trace elements
- Major Cat- and Anions and pH used as input variables
- Concentration of trace elements as output variables



DASHTI ET AL., (UNDER REVIEW)

# Motivation – From exploration to application

## ■ What we learned so far:

### ■ Data quality reflects model quality

- Comprehensive hydrochemical data sets are expensive and require a lot of effort to generate

- Usually only a portion of the chemical system is investigated

### ■ Data processing is more important than model tuning

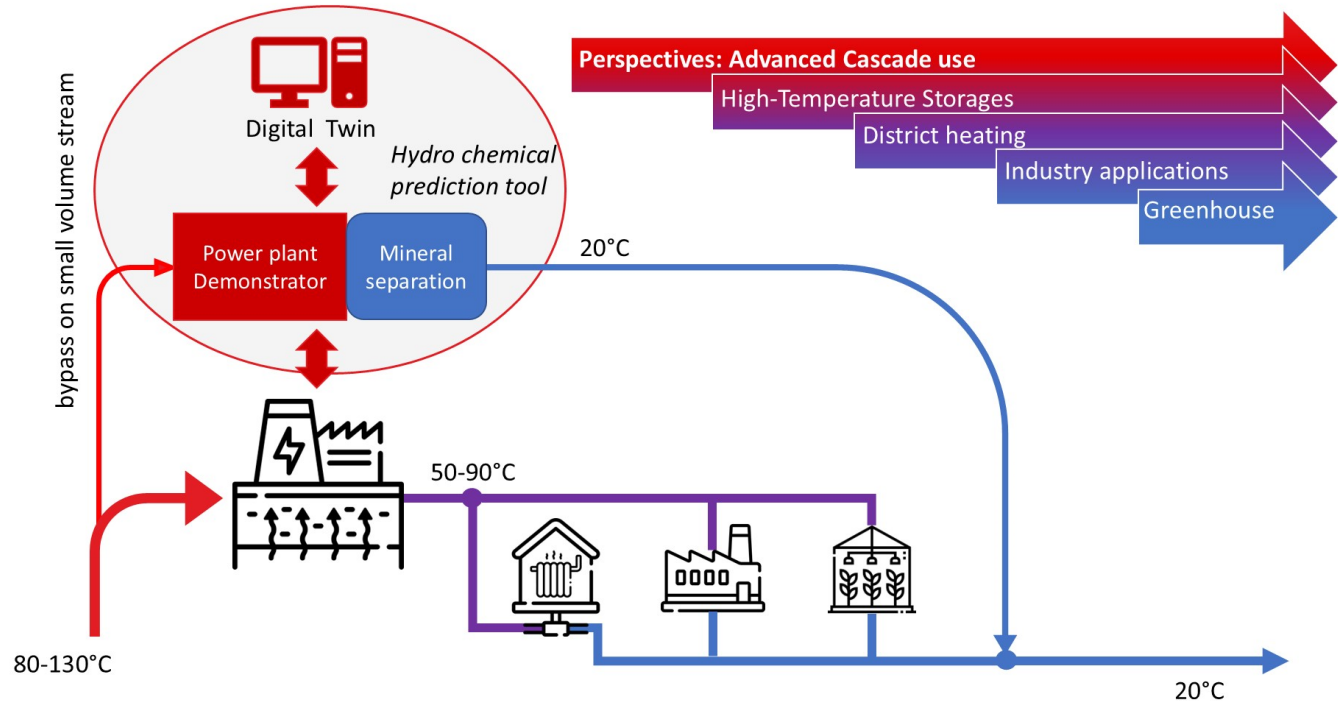
### ■ Datasets with 75 entries can be sufficient for machine learning in geochemistry

### ■ Data set distribution becomes very important when handling small data sets

 Translate knowledge into operation of geothermal power plants

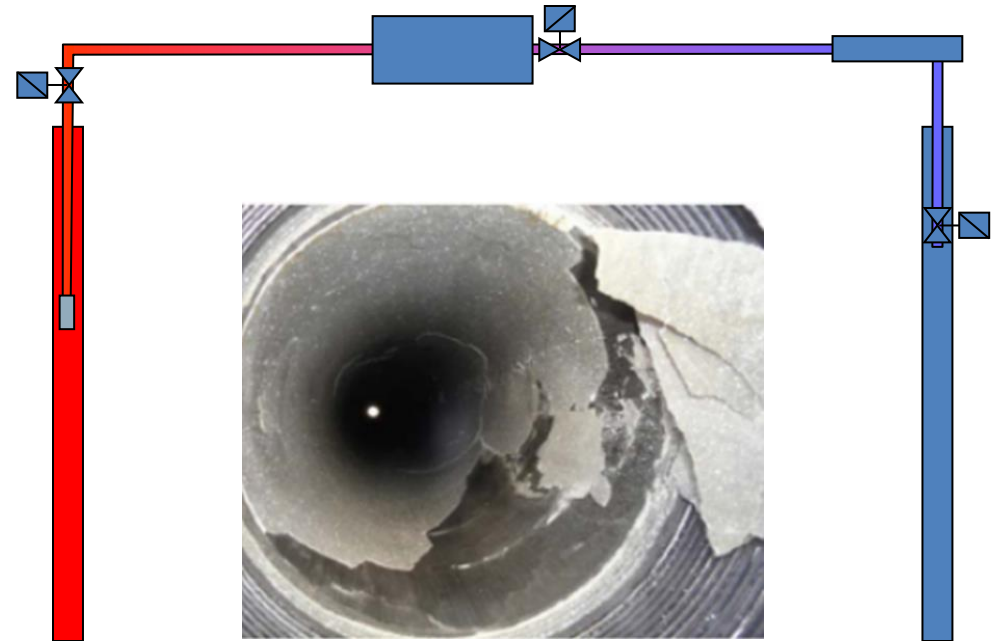
# The idea

- Using AI to control the occurrence of scaling and degassing
- Increased  $\Delta T$  for cascade use and heightened heat extraction efficiency
- Technological challenges with pressure maintenance in cascade use



# Pressure maintenance

- Pressure level maintenance throughout the power plant cycle
- Formation of a free gas phase can lead to carbonate scaling, chemical corrosion or abrasion corrosion
- The system boundaries are not clearly defined, and there is a significant security factor involved in maintaining pressure.



WANNER ET AL., 2017

# Experiment locations



Unterschleißheim, Germany



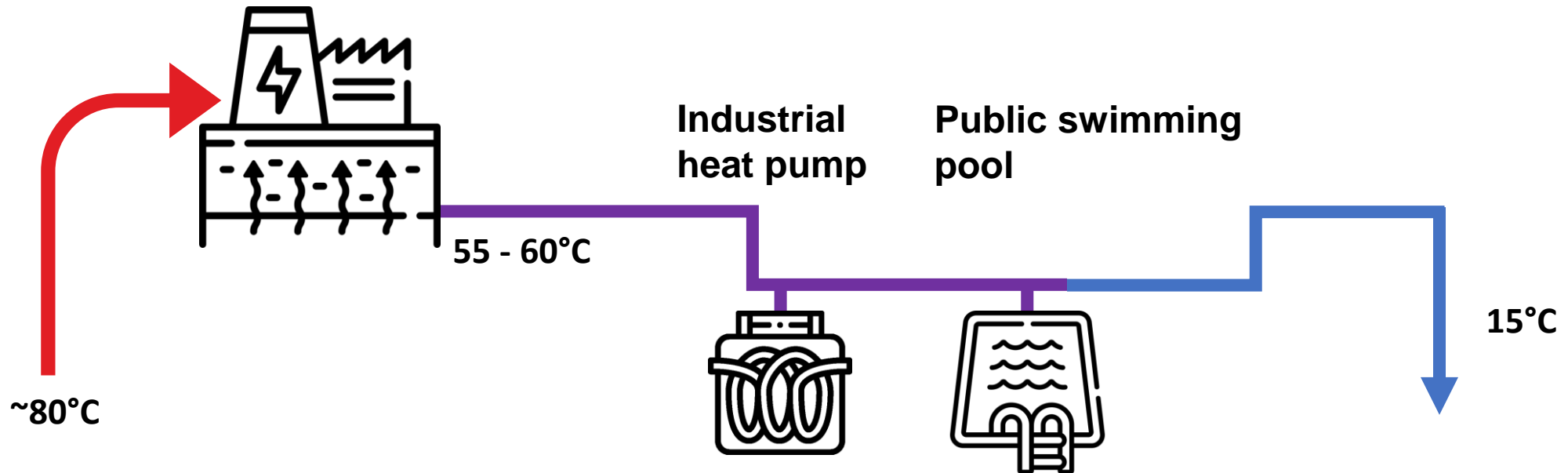
Haag am Hausruck, Austria



Gülpınar, Türkiye

# Cascade use example Unterschleißheim

Increase efficiency by implementing second heat extraction with an industrial heat pump prior to using brine in a thermal bath.





# Hardware-Twin – on-site demonstration unit

- Demonstrator for continuous geochemical monitoring
  - Mobile unit, deployable in the field
  - Coupled directly to the power plant
  - Emulation tool for geochemical processes in a geothermal power plant
- Controlling of temperature, pressure, pH and flow rate allow on-site degassing, scaling and corrosion experiments



*Hardware-twin while testing at the Fraunhofer ISE*

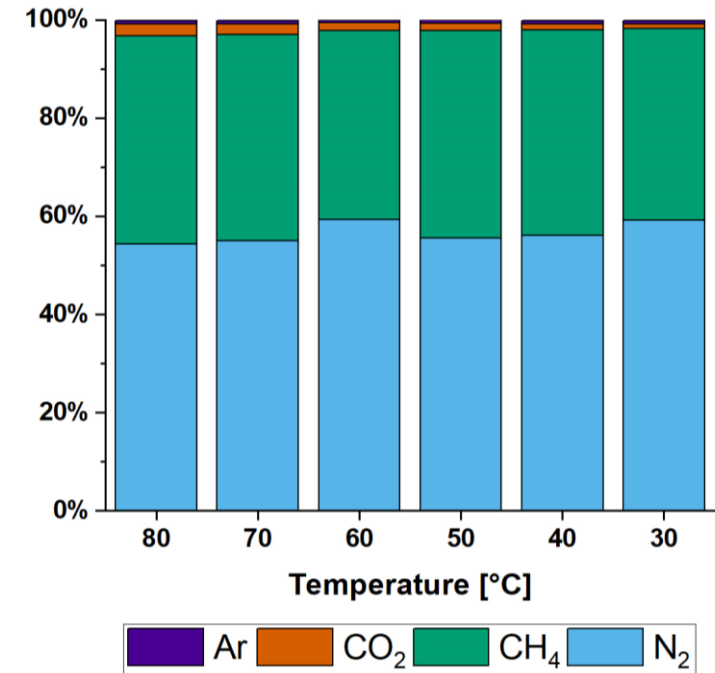
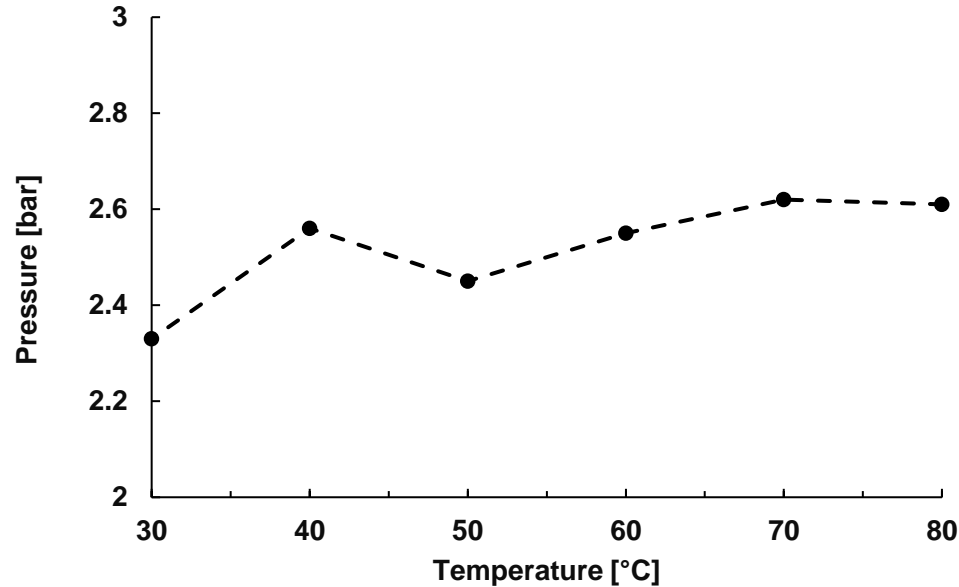
# In-line degassing experiments

- Investigating degassing processes of the geothermal fluid under in-situ conditions
- The inlet pipe extends almost to the top within the cylinder.
- Outlet at the bottom
  - Gravity traps gas bubbles
- Observation of gas level through sight glass
- Sampling port and overpressure valve at the top



# Bubble point determination in USH

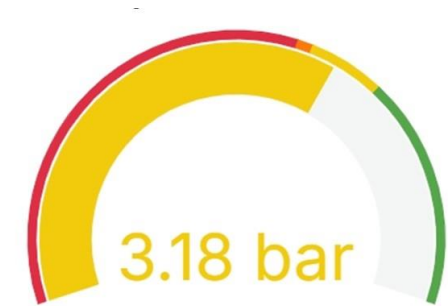
- Investigating the bubble point in dependance of temperature
- Defining boundaries for the digital-twin



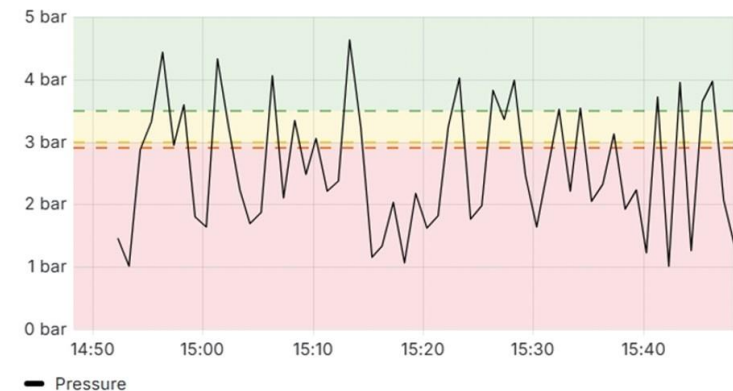
# Digital twin

- Cloud based geochemical modelling environment via PHREEQC
- Data of over 50 sensors are written in real time in a cloud database
- PHREEQC scripts are run at one-minute intervals to determine the scaling and degassing potential under the current hydrochemical conditions measured by the sensors
- Depending on the modelling results, the demonstrator's flow rate and pressure can be controlled dynamically by an AI.

Pressure gauge

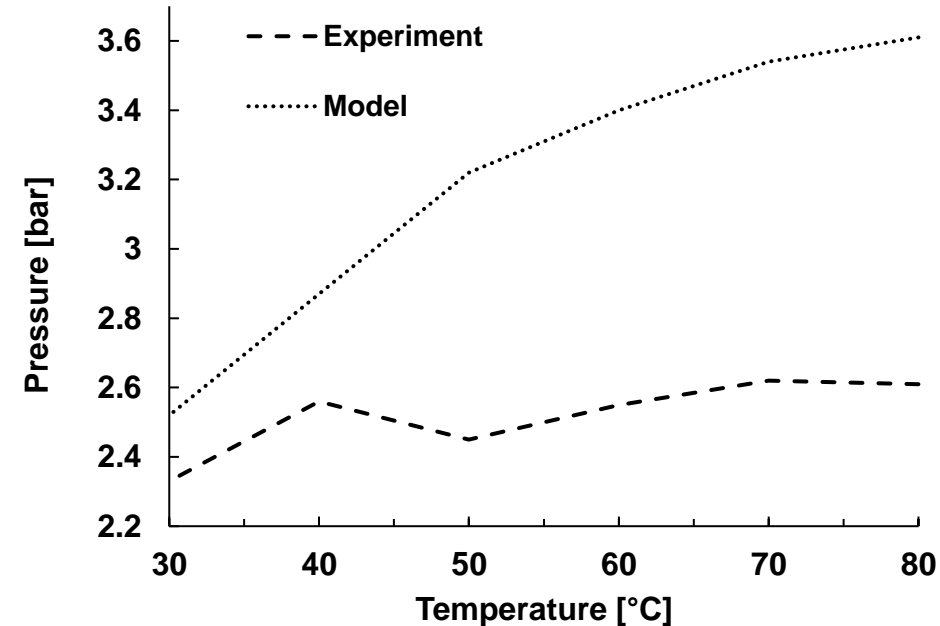


Time series on artificial data for benchmarking



# Automatization for hydrochemical big data

- Automatization of gas trap data generation
- Geochemical models do not consider all the relevant parameters
  - Biggest challenge is the data distribution across the variation of degassing controlling chemical parameters (Temp., pressure and pH)
- 3D parameter space needs to have data spread evenly across all three dimensions to prevent the machine learning model from being biased



# Summary

- Artificial intelligence can provide valuable support during the exploration phase of a geothermal power plant.
- Machine learning models struggle to grasp chemical processes since an equal amount of data is required for every system state.
- Developed a mobile tool to overcome the aforementioned challenges and generating comprehensive data sets for machine learning models to support the operation of geothermal power plants

# Thank you for your kind attention



Machine Learning for Enhancing Geothermal Energy



Federal Ministry  
for Economic Affairs  
and Climate Action

# Locations & their issues

## ■ Haag am Hausruck:

- Clocking of filter systems at the decentral heat pumps of the customers with organic compounds followed by microbial growth

## ■ Unterschleißheim:

- Increasing the heat extraction rate with an industrial heat pump to cool down the brine by 5 more °C after the heat exchanger
- Investigate the scaling potential if there is no pressure maintenance

## ■ Gölpinar:

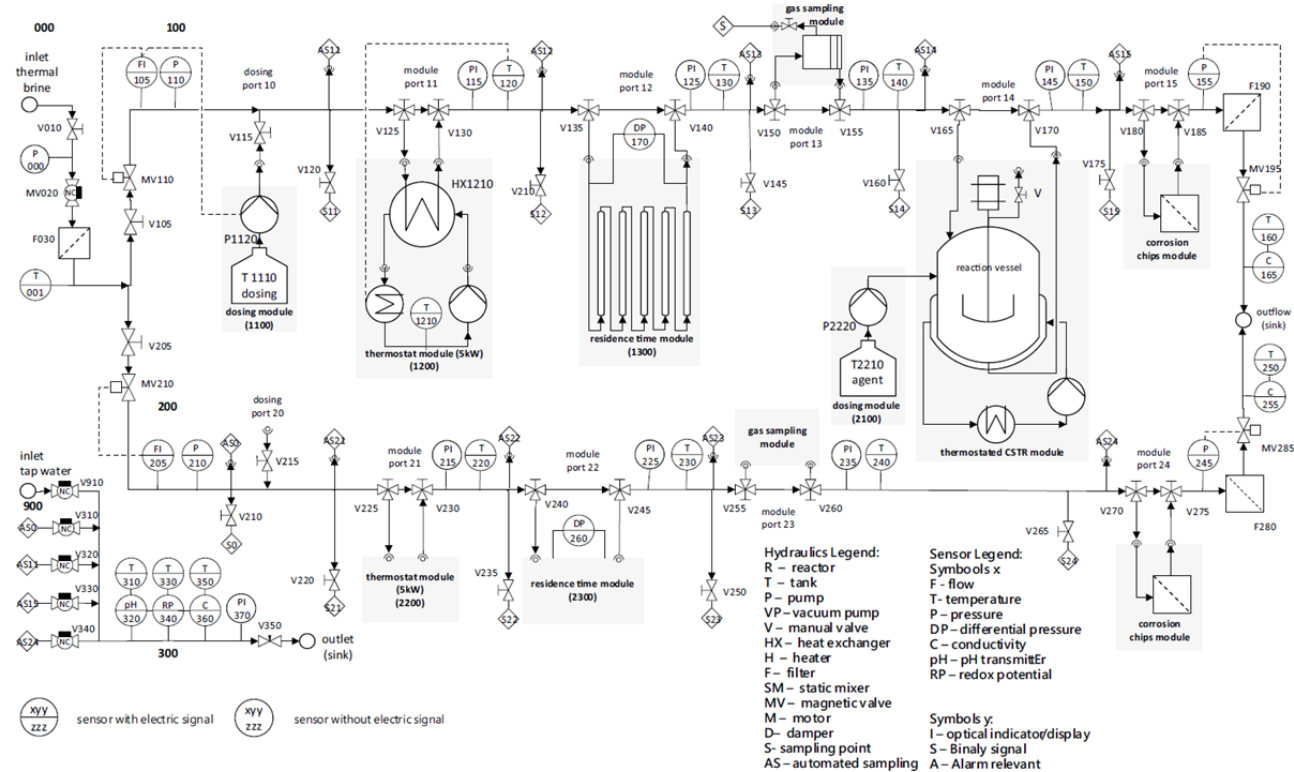
- Reducing the maintenance pressure from 20 to 10 bars
- Testing different scaling prevention methods



# Hardware-Twin in the field



# Hardware-Twin - Features



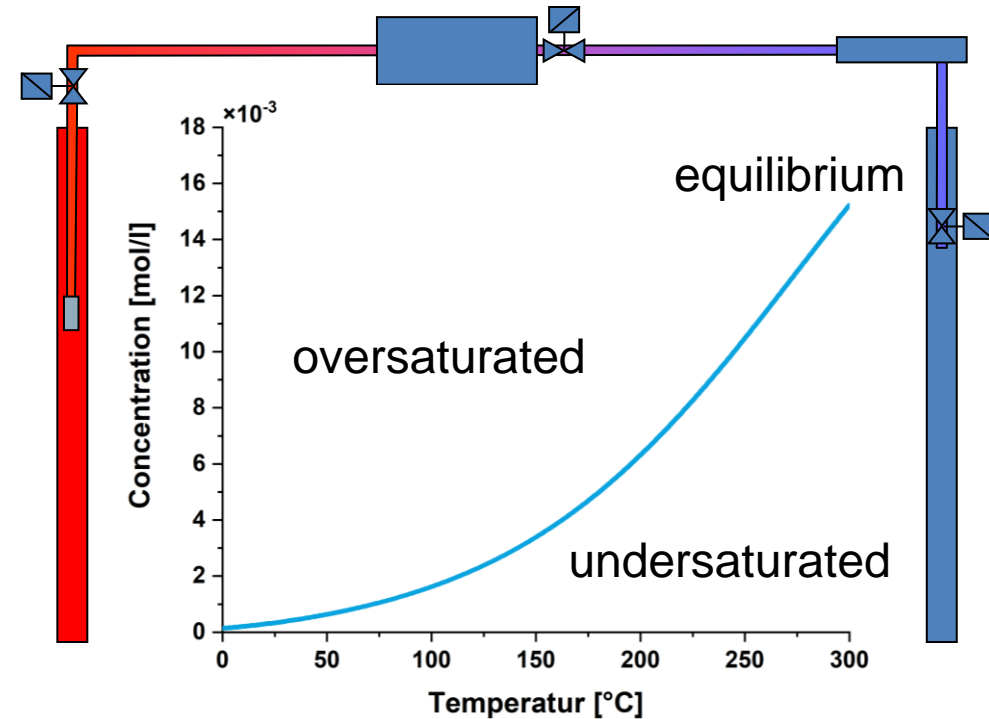
# Planned experiments in Gölpinar

- Degassing experiments: Investigate bubble point and gas content in dependence of temperature and flow regime
- Scaling occurrence: Investigate mineral precipitation in harsh pH and temperature conditions. pH between 3 and 10 and temperature down to 30°C.
- Monitoring of major cations, sulfate and trace elements.
- Isotopes in cooperation with Hydroisotop.

# Motivation - Scaling

Solubility is dependant on:

1. pH
2. Pressure
3. Temperature
4. Salinity



# Project & Partner

Funded by:



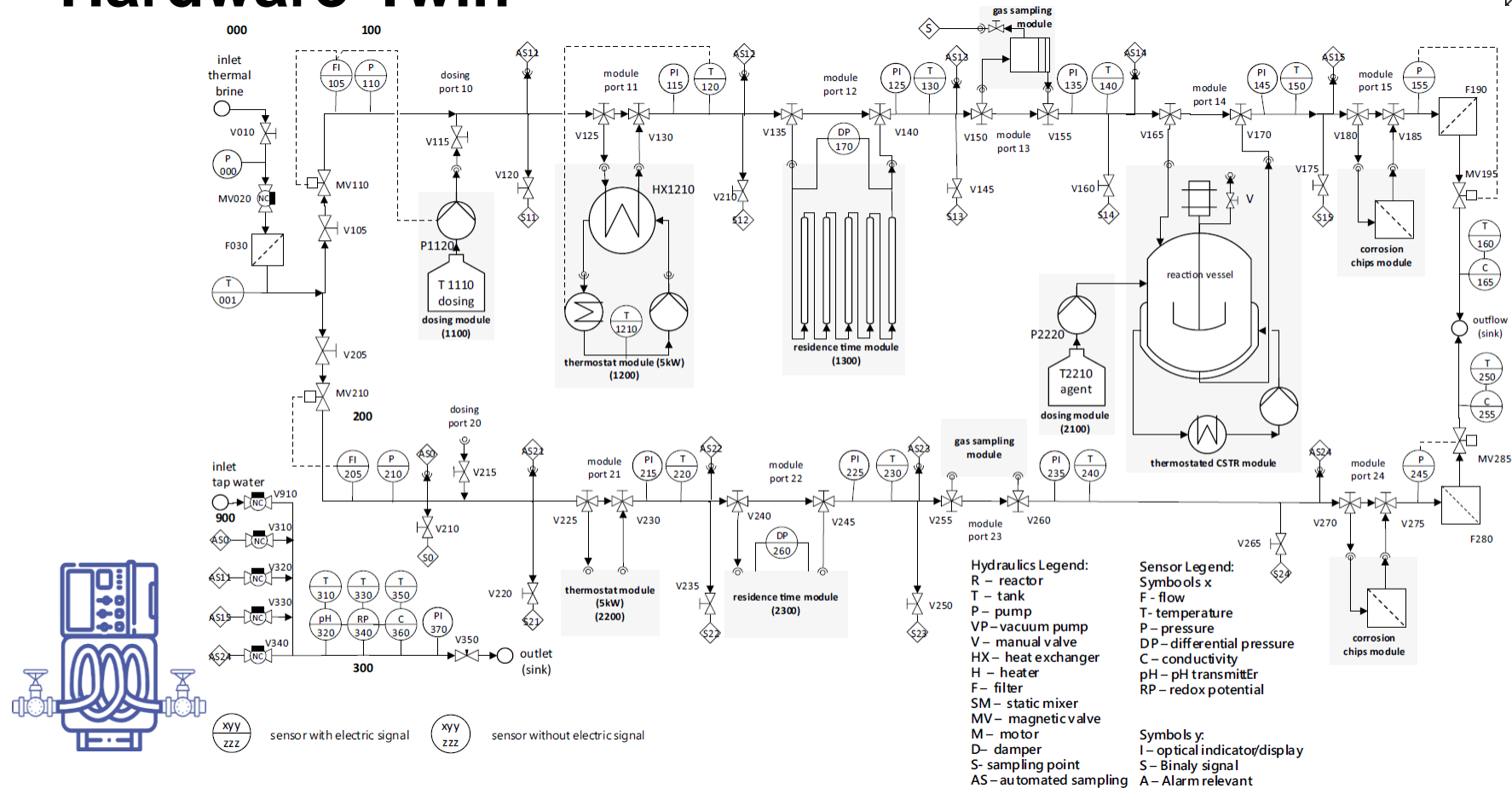
Started in 2022 until 2025

Funding volume: 1 788000 €

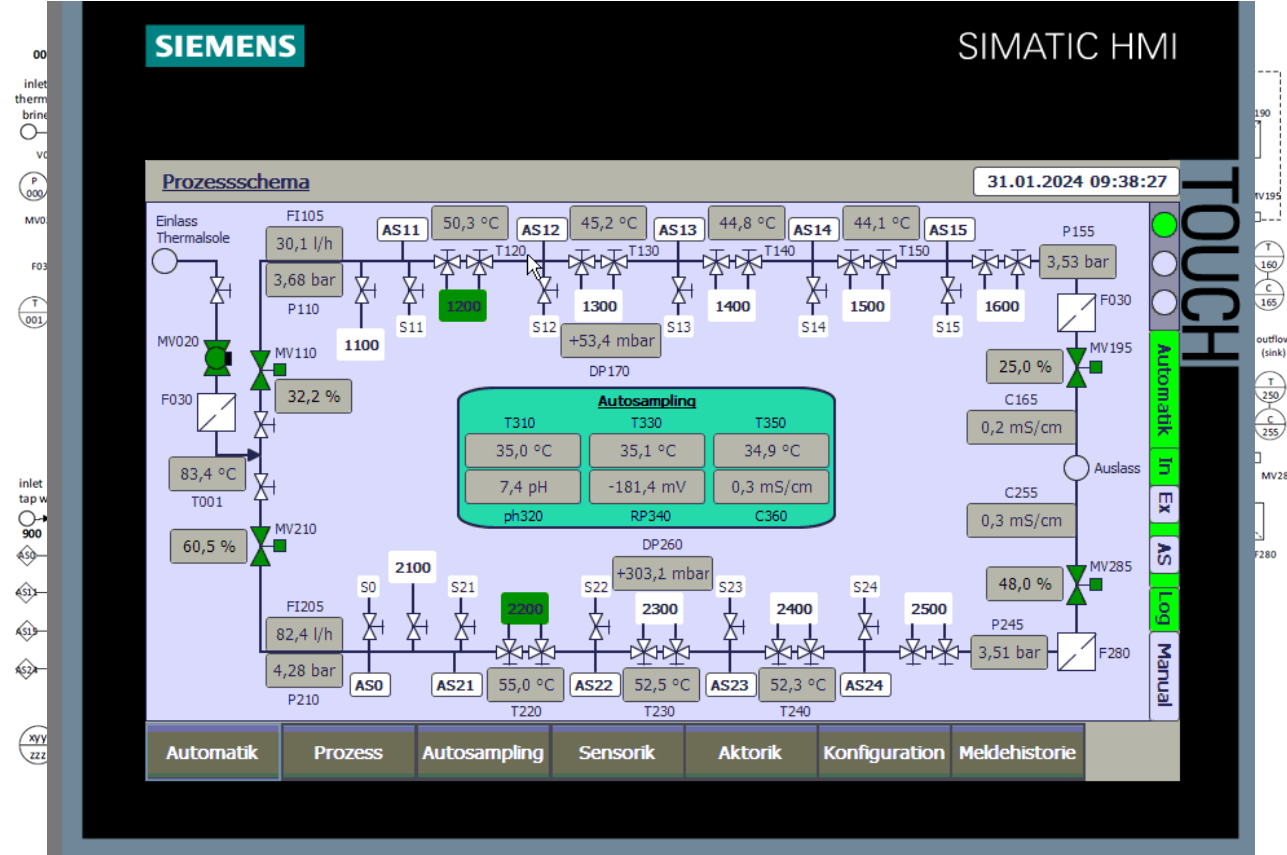




# Hardware-Twin



# Hardware-Twin - Features

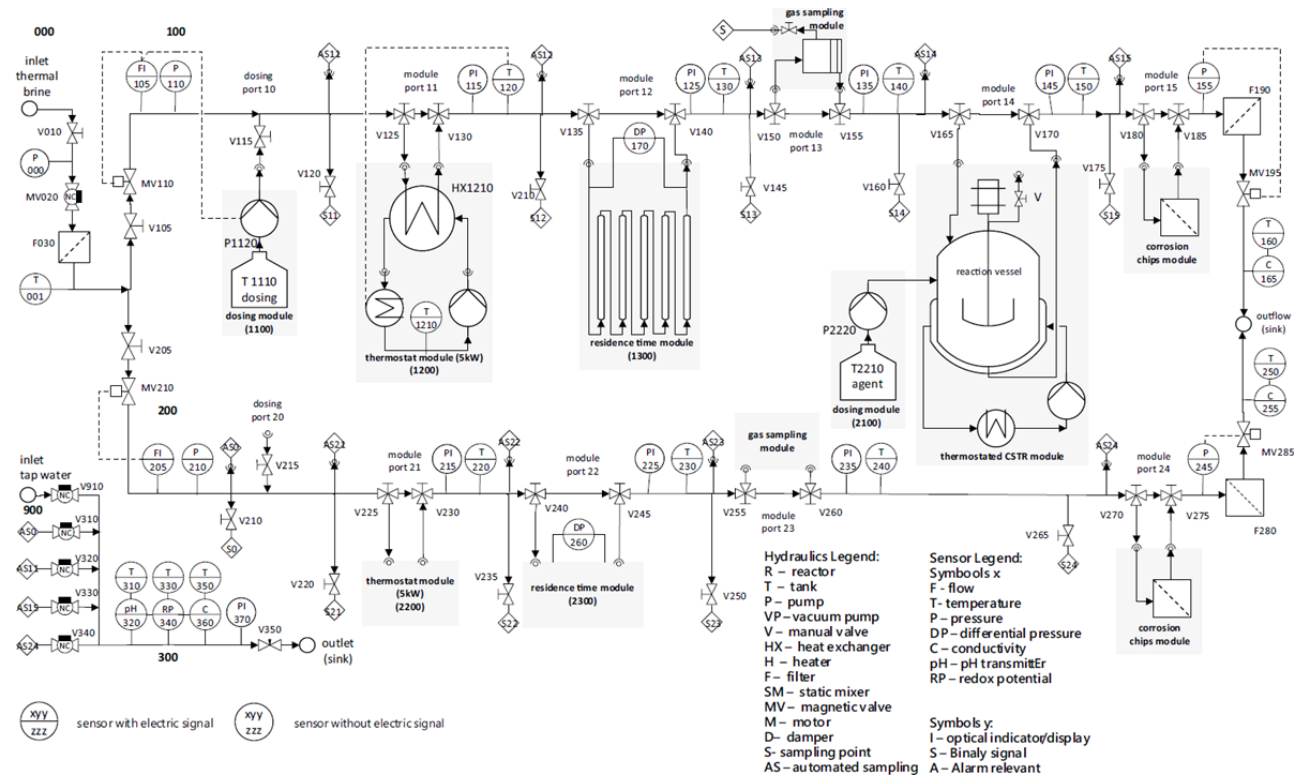


# The Team





# Hardware-Twin - Features

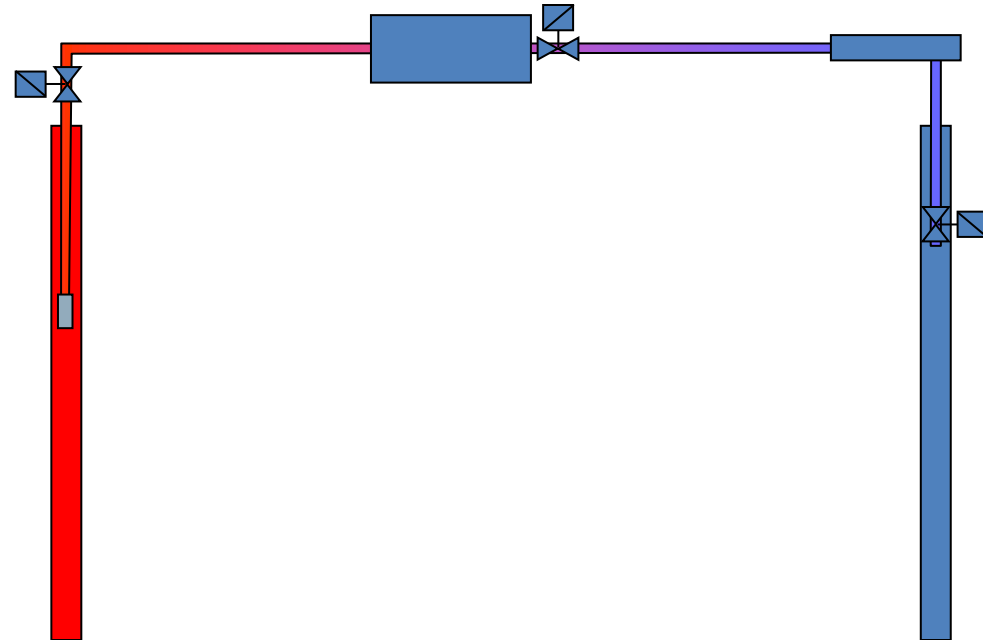


# Agenda

- Project & Partner
- Motivation
- The Idea
- Concept
- Implementation of Artificial Intelligence

# Motivation – Degassing & Corrosion

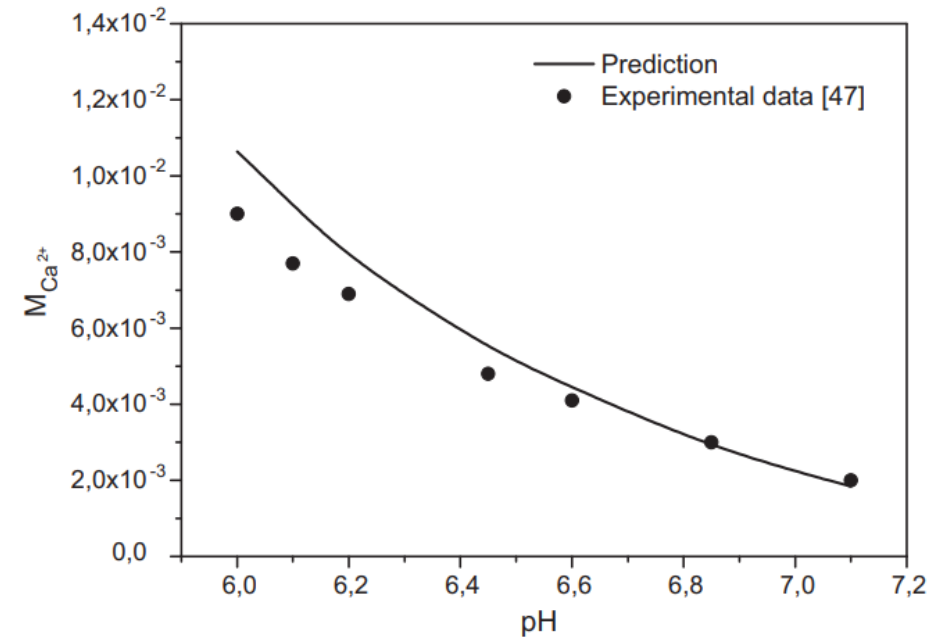
Silica scaling here!



# Carbonate scaling

- Degassing results in loss of carbonic acid because it is in solution as dissolved  $\text{CO}_2$
- A shift in the carbonate equilibrium leads to higher pH
- Calcium solubility decreases with higher pH

 Carbonate scalings



COTO ET AL. (2012)

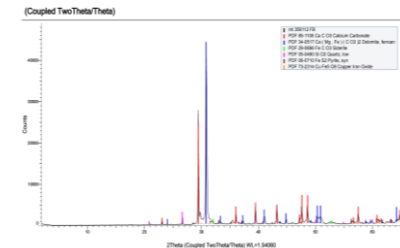
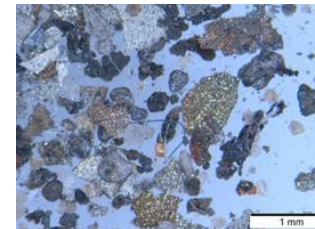
# Intensive hydrogeochemical sampling

## ■ Hydrogeochemical sampling campaign

- Fluid analyses of the geothermal brine include major elements, trace elements, common isotopes and gas phase
- Solid analyses of suspended particles and scaling via SEM, XRF, XRD....



➔ Hydrogeochemical data for deterministic modelling



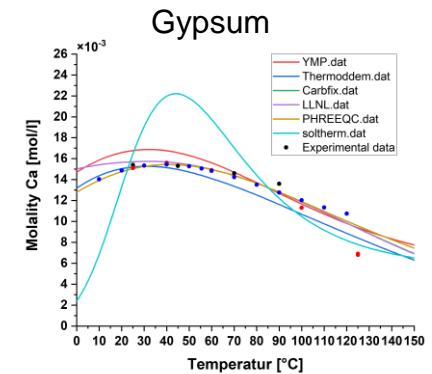
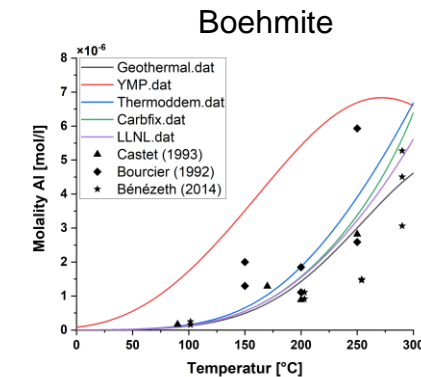
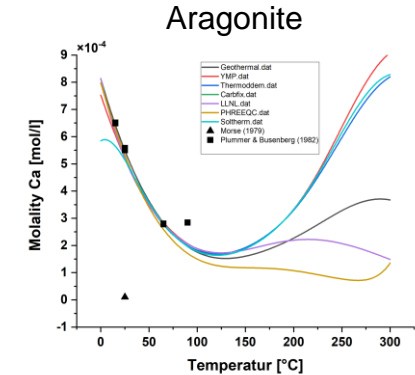
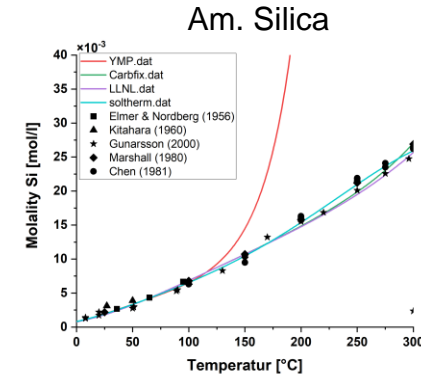
# Thermodynamic databases

## Validation of thermodynamic data

- Compilation of a valid thermodynamic database in PHREEQC
- Comparison with literature data (Experiments and verified thermodynamic models)



Improvement of deterministic calculations and models



# Digital-Twin

## ■ Deterministic modelling

- Deterministic adaptation of power plant parameters (temperature, pH, pressure)
- Modelling of degassing, scaling, and corrosion potential

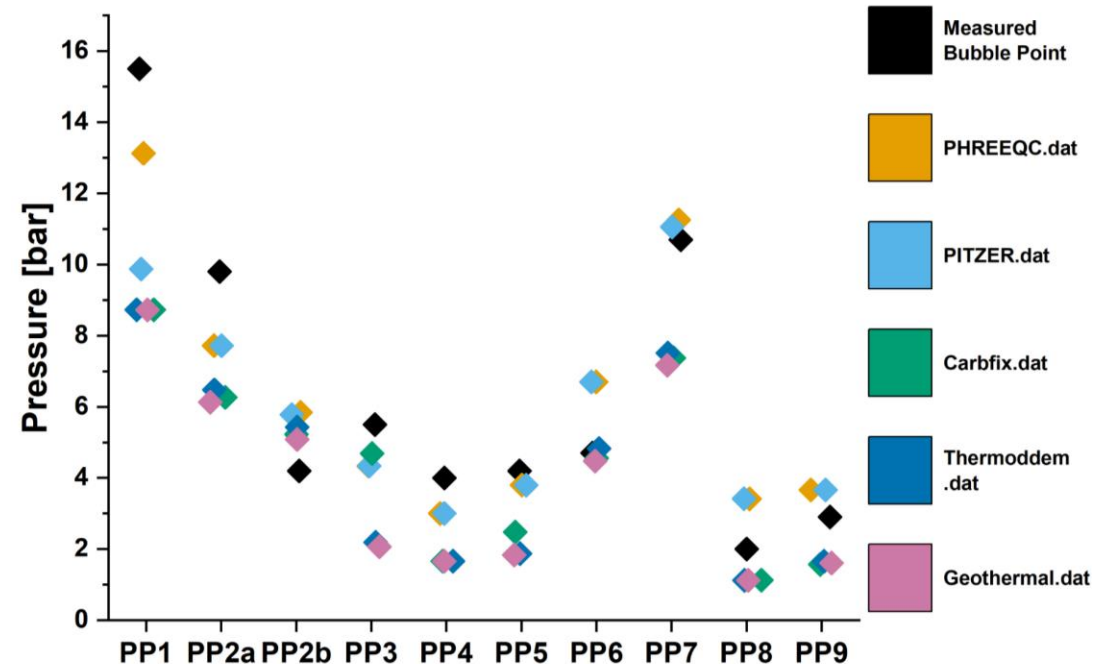
```
% For-loops of the several sensitivity analyses calculated via IPhreeqc
for bb = 1:bbb % nombre of pressure sensitivity steps
for cc = 1:ccc % number of steamloss/dilution sensitivity steps
for aa = 1:aaa % number of pH sensitivity steps
    iphreeqc = actxserver('IPhreeqcCOM.Object');
    iphreeqc.LoadDatabase(['C:\Program Files\USGS\IPhreeqcCOM' ...
        ' 3.7.3-15968\database\llnl.dat']); % pathname to IPhreeqcCOM
    iphreeqc.ClearAccumulatedLines;
    iphreeqc.AccumulateLine ('SOLUTION 1');
    iphreeqc.AccumulateLine (['-units ' con]);
    iphreeqc.AccumulateLine (['-temperature ' (num2str(...
        struct.Temperature))]);
    iphreeqc.AccumulateLine (['-pH ' (num2str(struct.pH))]);
```



Establishment of a huge dataset  
to train the artificial intelligence

# Bubble point modelling

- 5 thermodynamic databases (TDB)
- 2 TDBs use a special approach to exclude  $N_2$ ,  $CH_4$  and  $H_2S$  from redox reactions
- Dissolve the measured gas phase in the brine and gradually reduce the pressure until the bubble point is reached and a free gas phase is formed
- Comparison of the measured bubble point of different power plants (PP) with the modeled one from each TDB

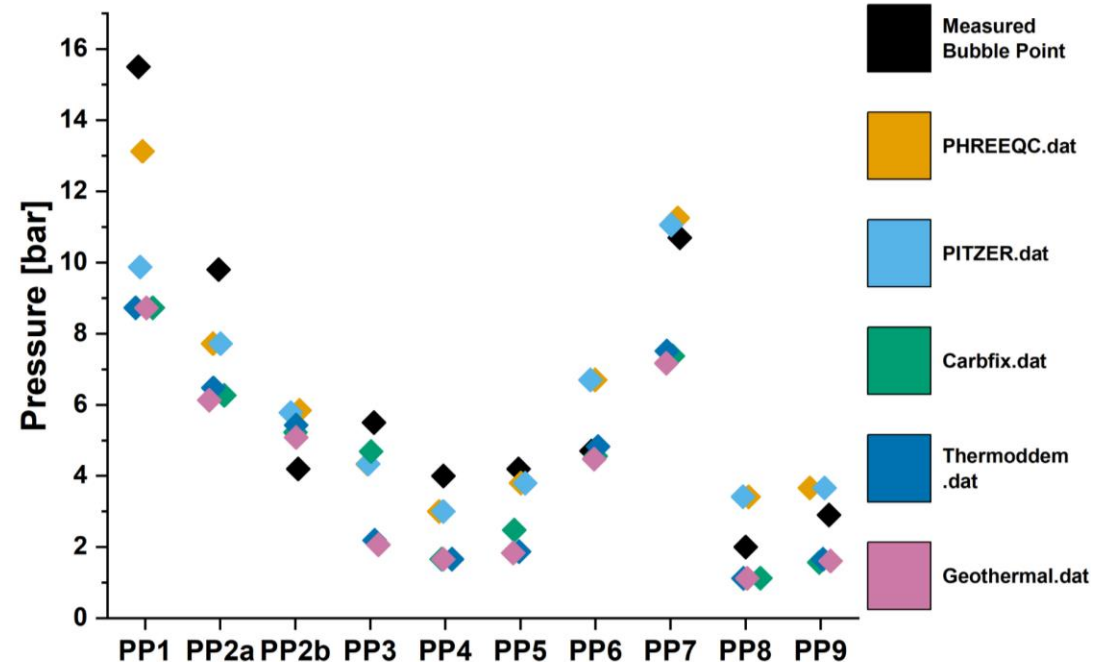




# Bubble point modelling

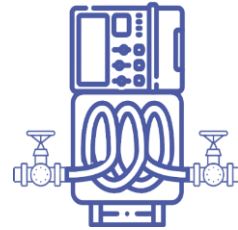
## Conclusion

- Tendency to underestimate the bubble point in the model
- Active redox reactions of the gas-forming species reduce the bubble point
- High uncertainties in the measured data, especially the bubble point
  - The bubble point is determined by in-situ observation in a pressure vessel until the formation of gas bubble is observed.
  - Flow regime – turbulent vs laminar



# Implementation of artificial intelligence

Use results to  
train AI



Safe analytic cost

**MALEG**



Compare hydro-  
geochemistry  
with AI model



Model hydrogeo-  
chemistry with live  
data feed

# References

- Christoph Wanner, Florian Eichinger, Thomas Jahrfeld, Larry W. Diamond, Causes of abundant calcite scaling in geothermal wells in the Bavarian Molasse Basin, Southern Germany, Geothermics, Volume 70, 2017, Pages 324-338, ISSN 0375- 6505
- B. Coto, C. Martos, J.L. Peña, R. Rodríguez, G. Pastor, Effects in the solubility of  $\text{CaCO}_3$ : Experimental study and model description, Fluid Phase Equilibria, Volume 324, 2012, Pages 1-7, ISSN 0378-3812, <https://doi.org/10.1016/j.fluid.2012.03.020>.