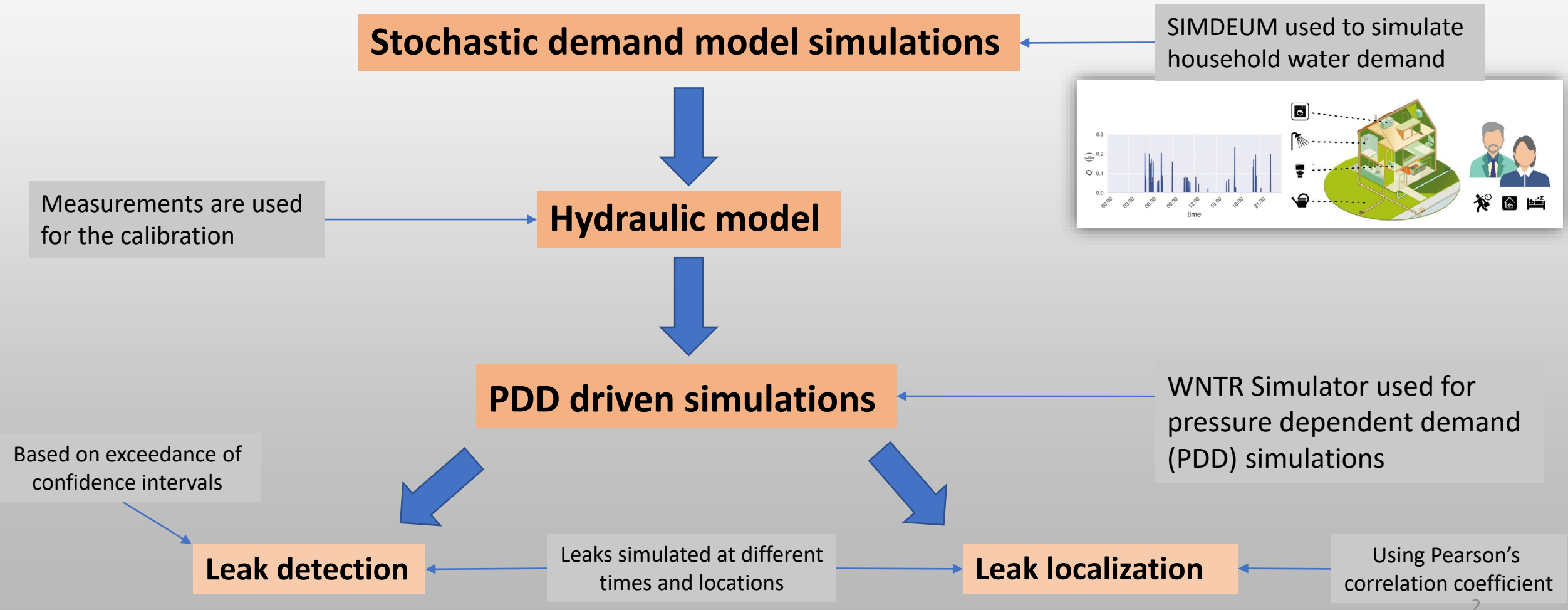




Fantastic leaks and where to find them

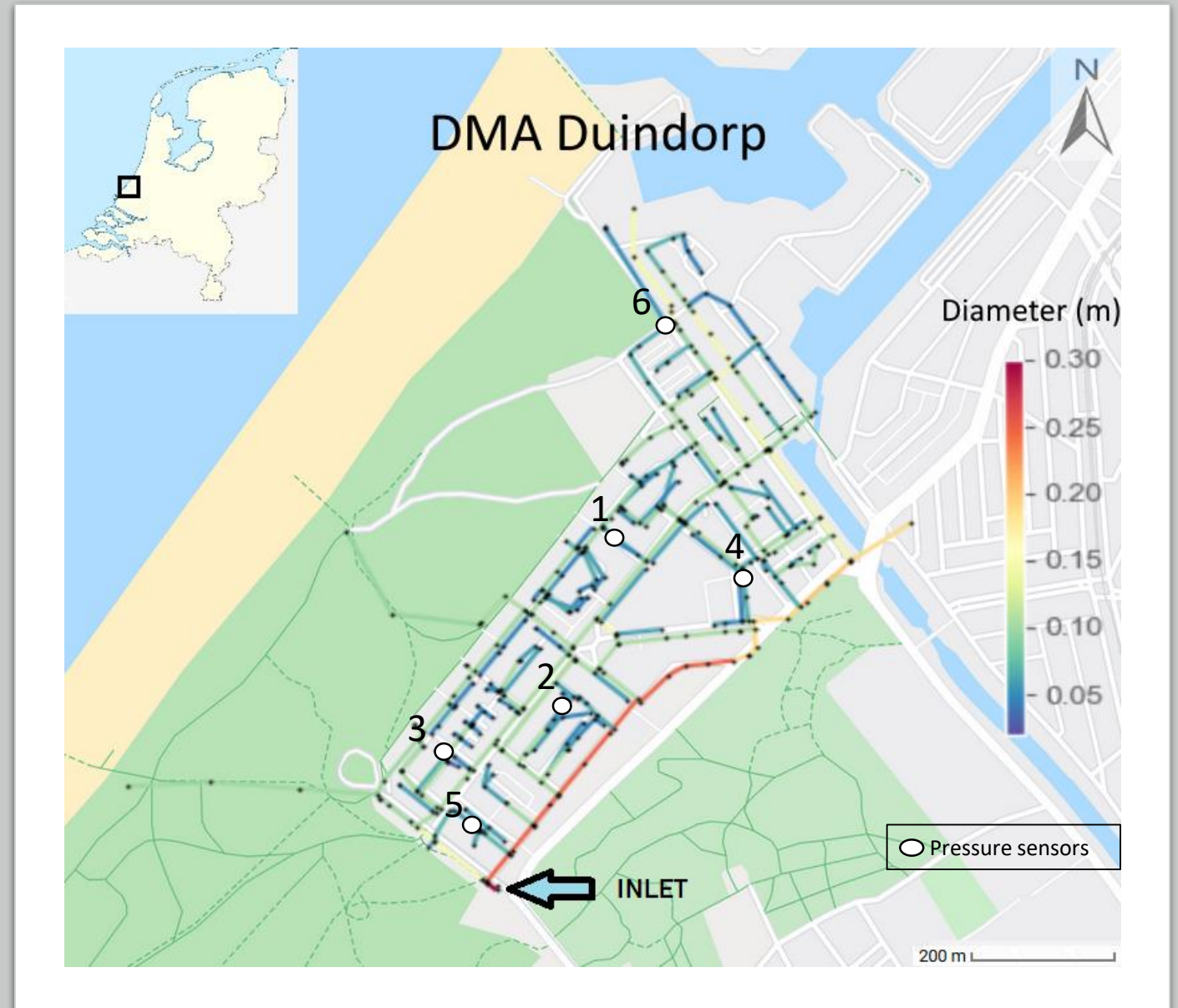
The influence of stochastic water demand
on leak detection and localization
in a water distribution network

The influence of stochastic water demand on leak detection and localization

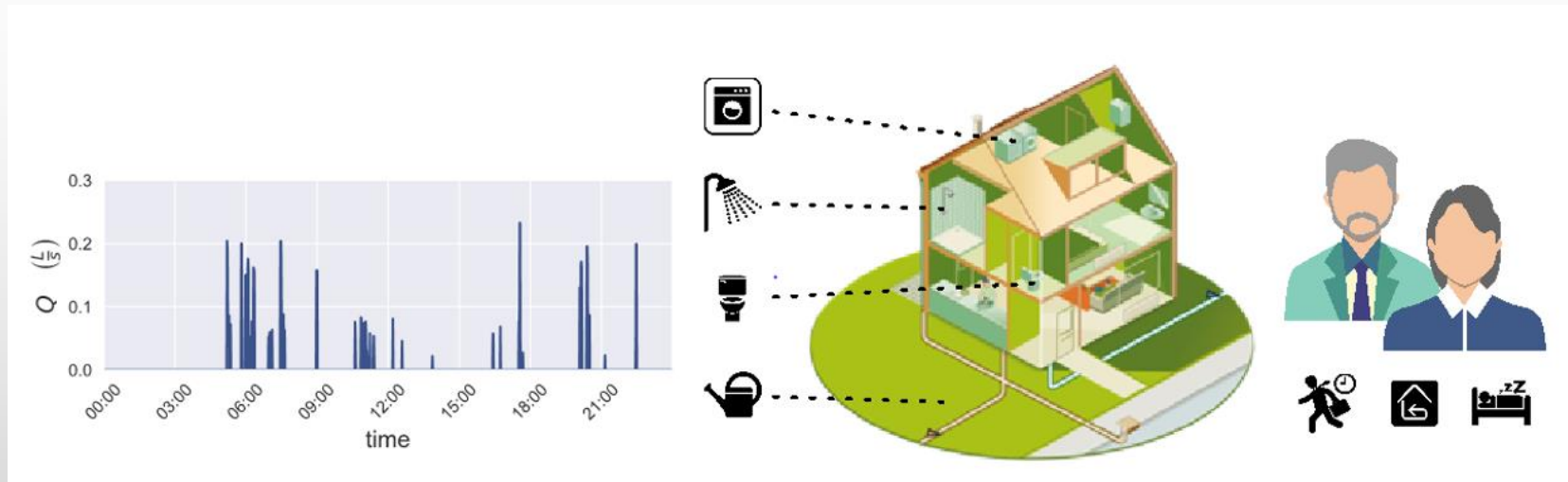



Research area: DMA Duindorp

- Area:
 - Mainly residence area
- Network:
 - length $\approx 14\text{km}$
 - 2825 connected households
- Sensors:
 - Pump: inflow and pressure
 - 6 pressure sensors in the area



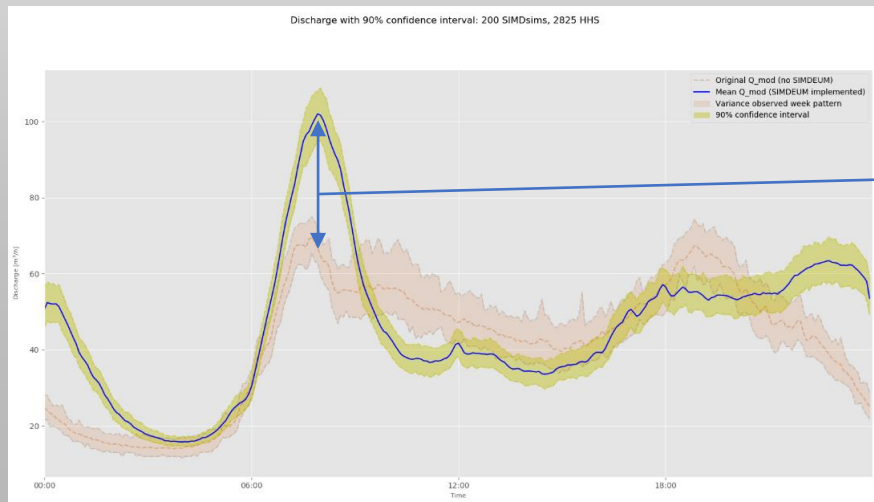
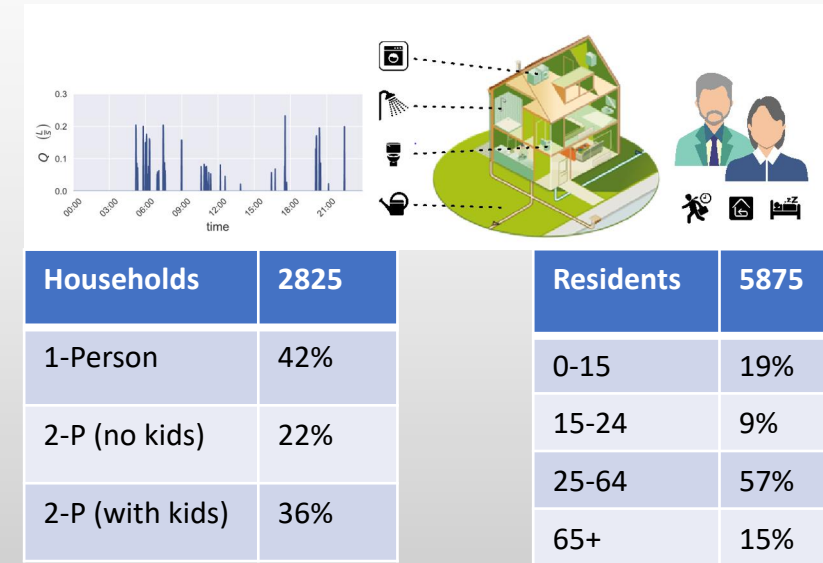
Simulating stochastic water demand



- Simulate water demand on household level based on:
 - Household statistics: residents, water-using appliances
 - Daily pattern of residents (work/sleep rhythm) based on survey data
 - Probability functions of use appliances throughout the day!
- Every single day simulation is therefore realistically different
- SIMDEUM will be used to create these water demands, model developed by 

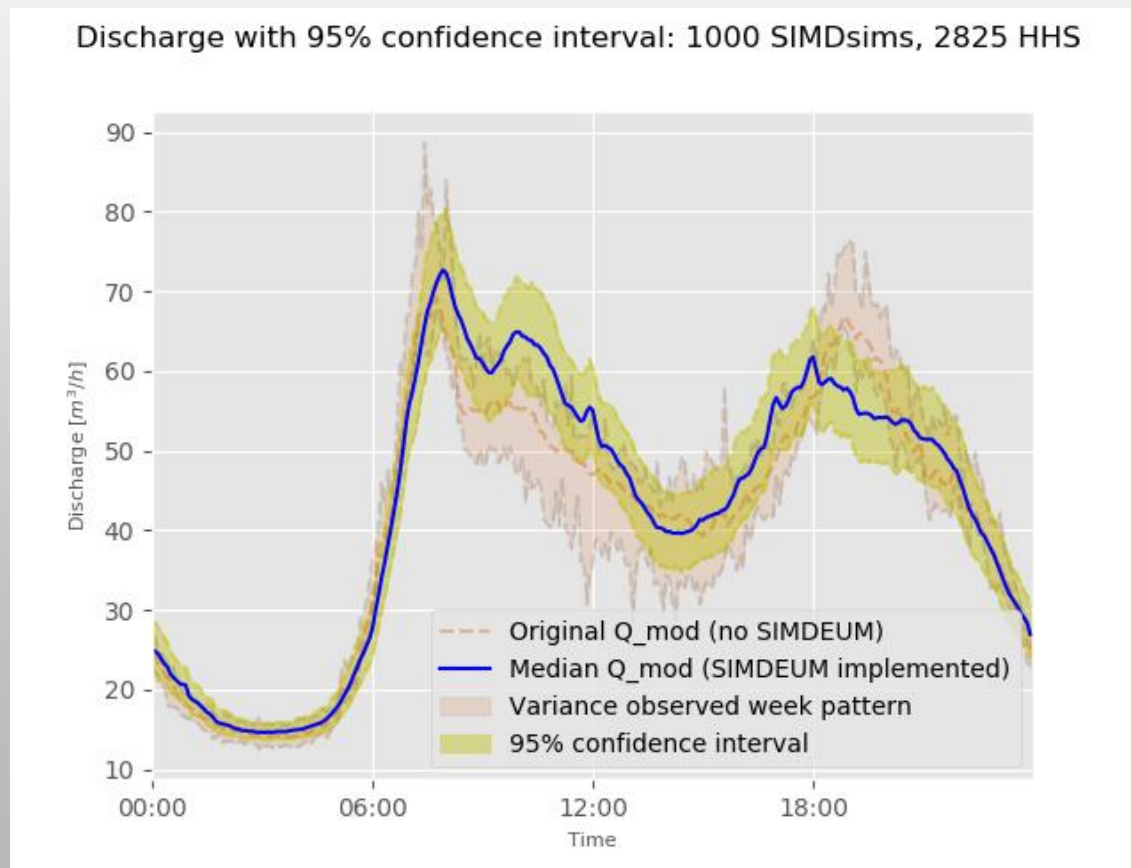
Simulating demand and feeding the hydraulic model

- [Data analysis and calibration hydraulic model: see Appendix]
- Implement statistics Duindorp and simulate demand
 - Default settings based on average Dutch statistics from 2014
 - Simulating average weekdays (excluding weekend)
 - 2825 households · 1000 day simulations
- Simulated demand patterns connected to nodes in hydraulic model based on billing information



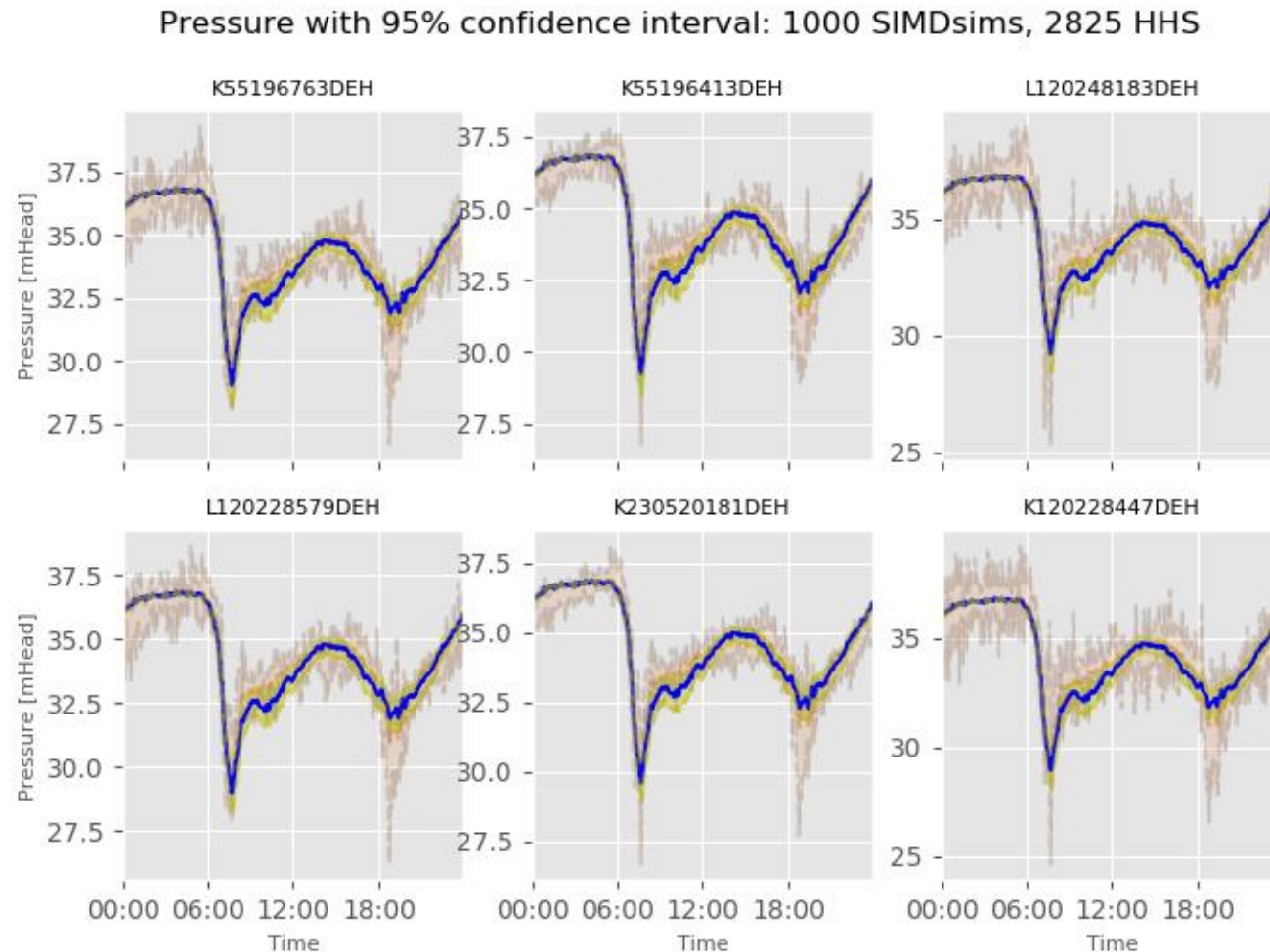
- Computing the inflow DMA and comparing with the measurements
 - Large differences of e.g. 30m³/h during morning peak!
- Extra modification settings demand simulator needed

- Observed inflow different than model with stochastic demand predicts
- Fitting procedure: modify SIMDEUM settings
 - Modify diurnal patterns of residents/ employment rate (people more at home during the day, hence water use increases)



- Yields in a much better fit
- However, not perfect and unrealistic changes are made to SIMDEUM
 - E.g. residents sleep 3 hours more than average
- Observed variance larger than what model with implemented SIMDEUM predicts

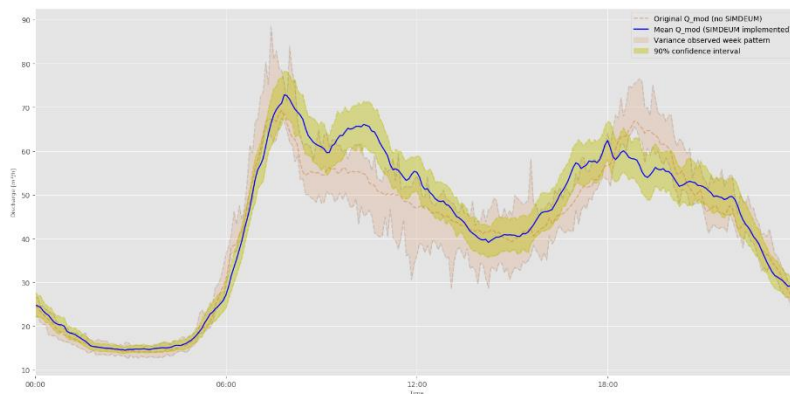
Results for the 6 pressure sensors



- Red: mean and variance of the observations
- Blue/yellow: 1000 simulations model with stochastic demand implemented, mean and variance of these simulations
- Observed variance a lot larger than prediction SIMDEUM

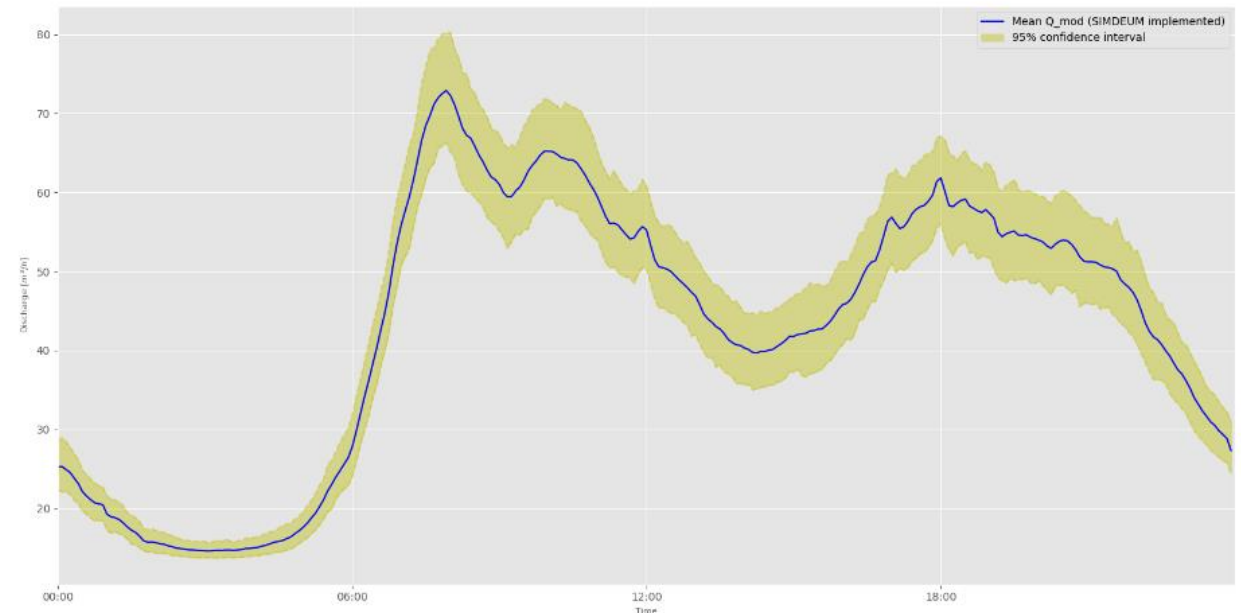
- Structural difference between observations and model with stochastic demand cannot be overcome
 - This will influence the leak detection and localization
- Therefore, for research purposes, neglect the observations for now
 - Assumption: model with the modified SIMDEUM settings is able to mimic network accurately enough

Discharge with 90% confidence interval: 100 SIMDsims, 2825 HHS



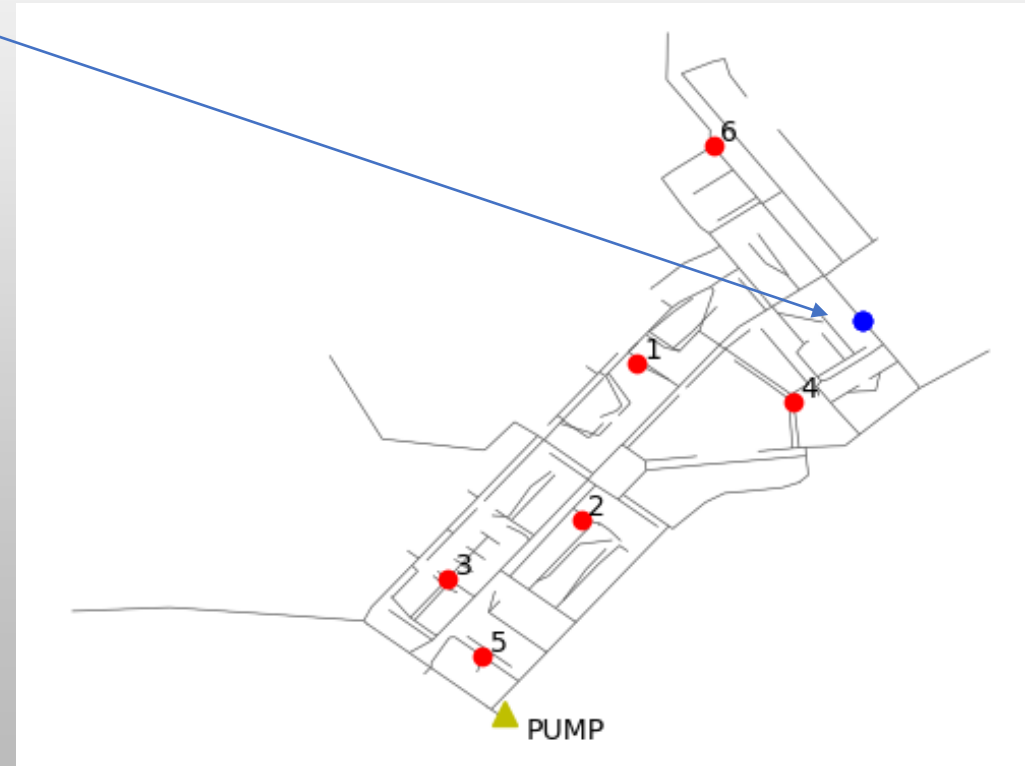
Inflow

Discharge with 95% confidence interval: 500 SIMDsims, 2825 HHS



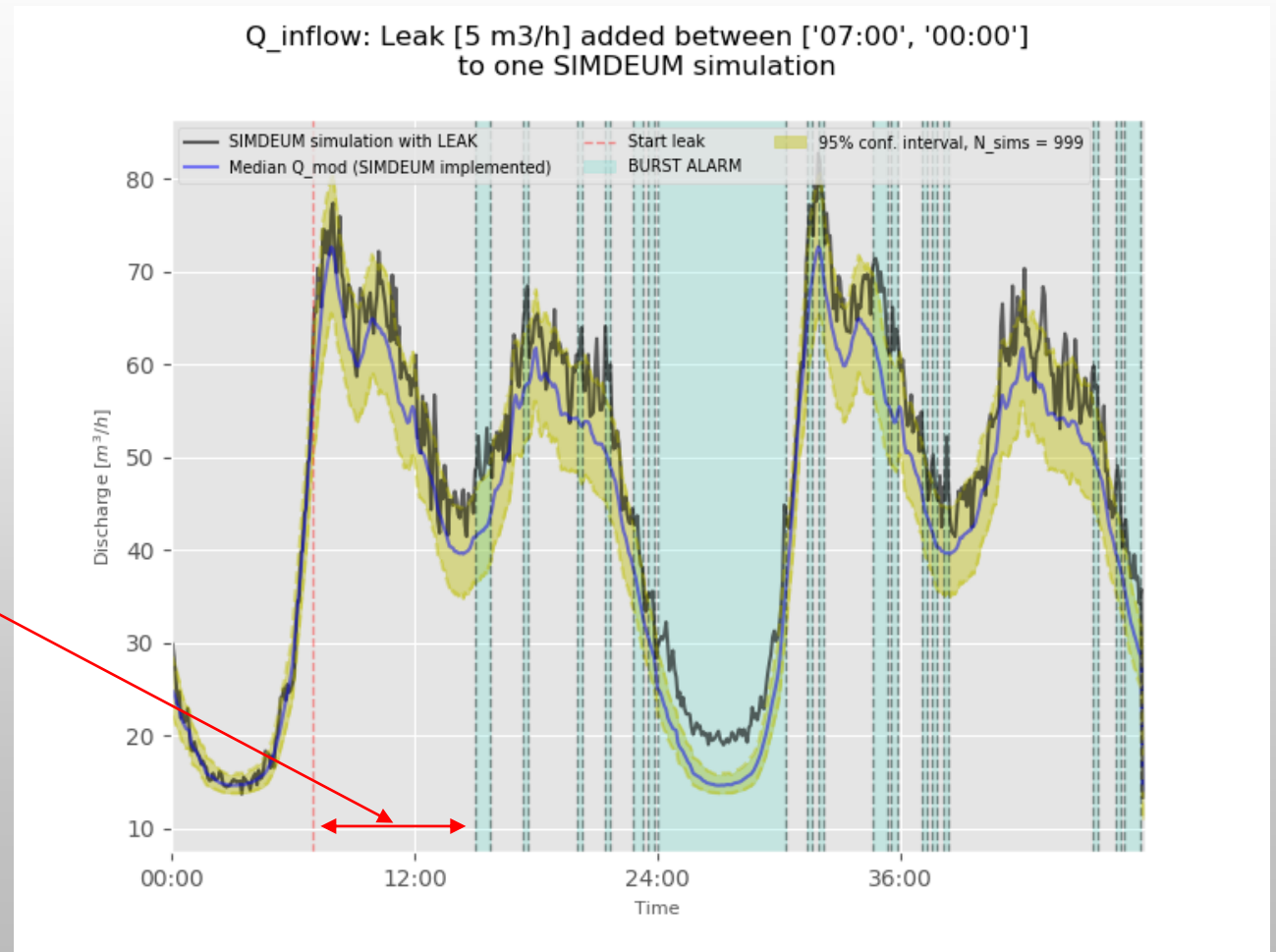
Results: LEAK DETECTION

- Run a random simulation of 2 days with stochastic demands
 - add a leak to the model
 - $Q_{\text{leak}} = 5\text{m}^3/\text{h}$
 - Start leak: 07:00



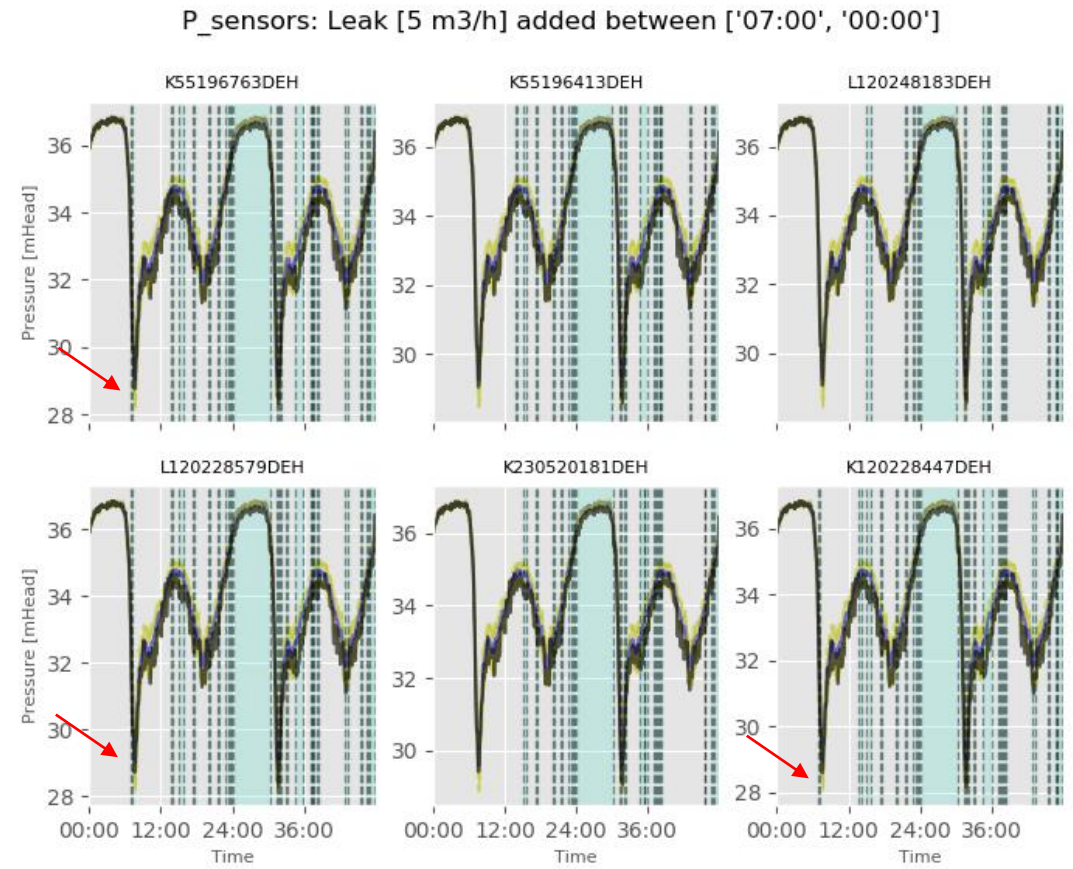
Leak detection: Simulated inflow results

- Alarm raised if 20min consecutively outside 95% confidence interval
- First alarm raised 4 hours after start of the leak

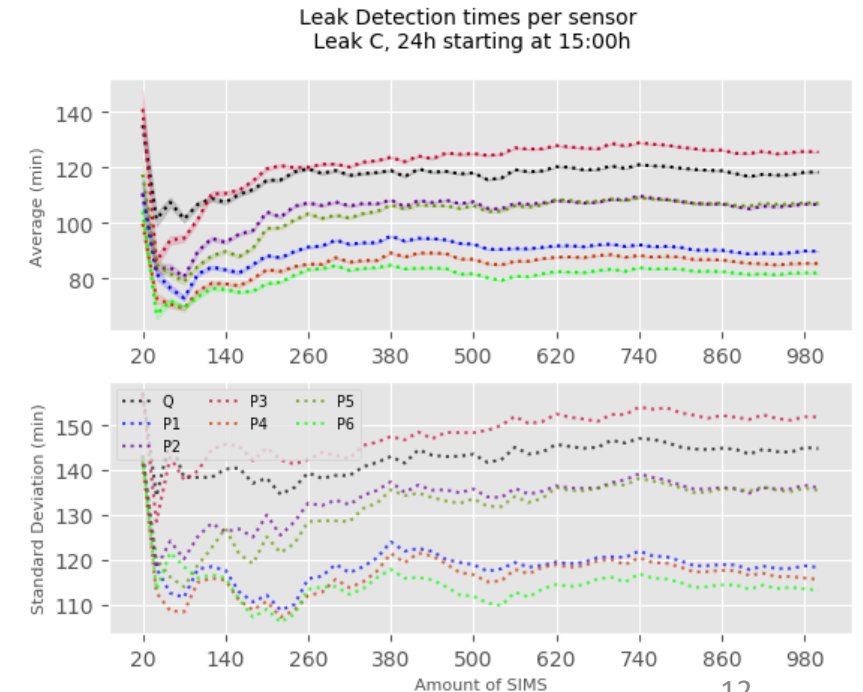
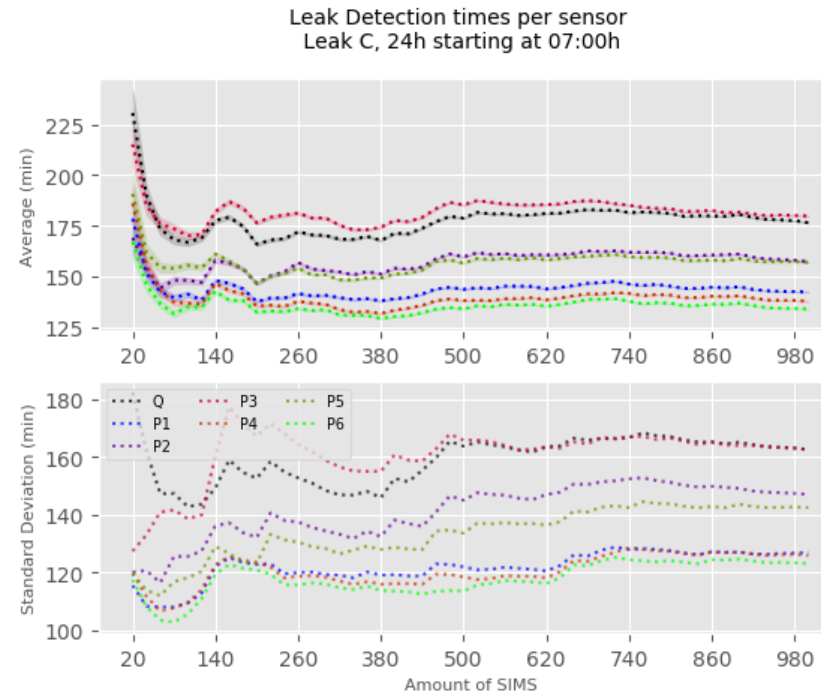
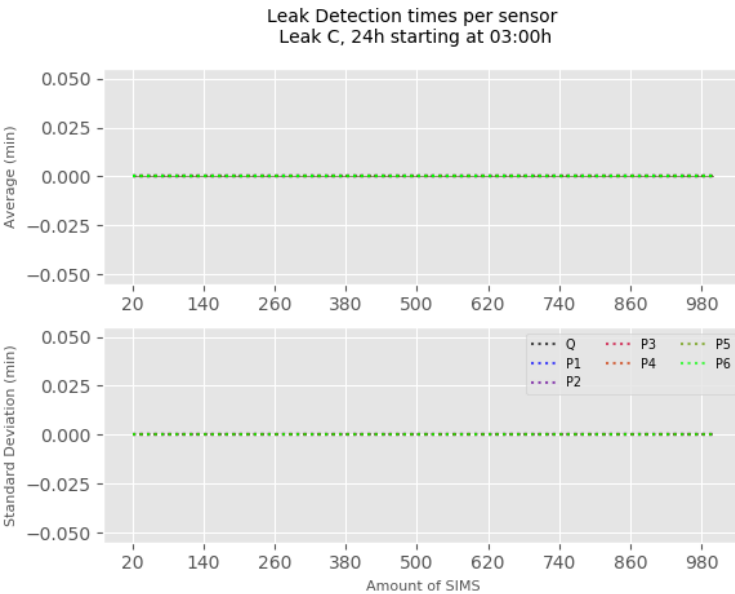
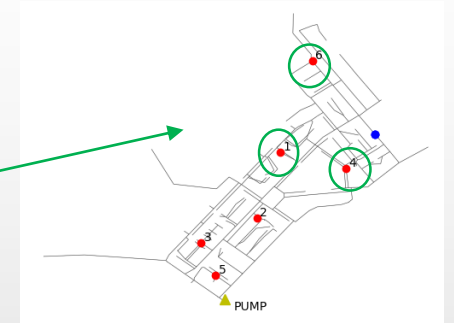


Leak detection: simulated pressures at sensors

- The same detection procedure for the pressure sensors
 - Using the same simulation as before
 - 3 out of 6 pressure sensors are more sensitive; earlier detection

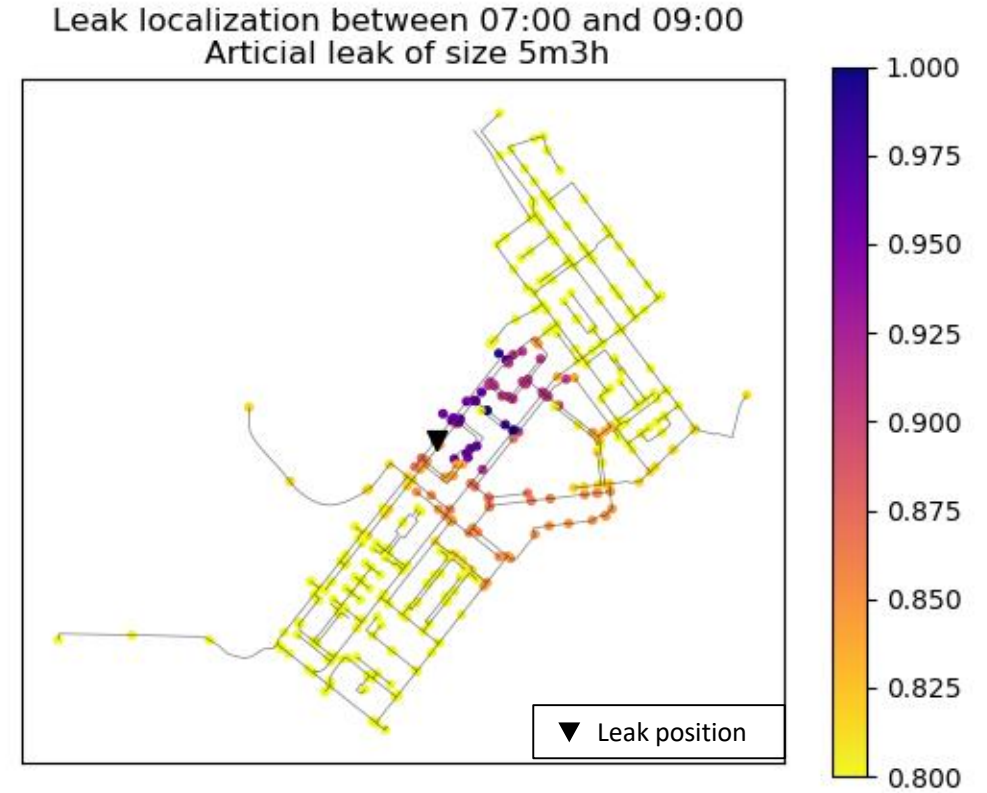
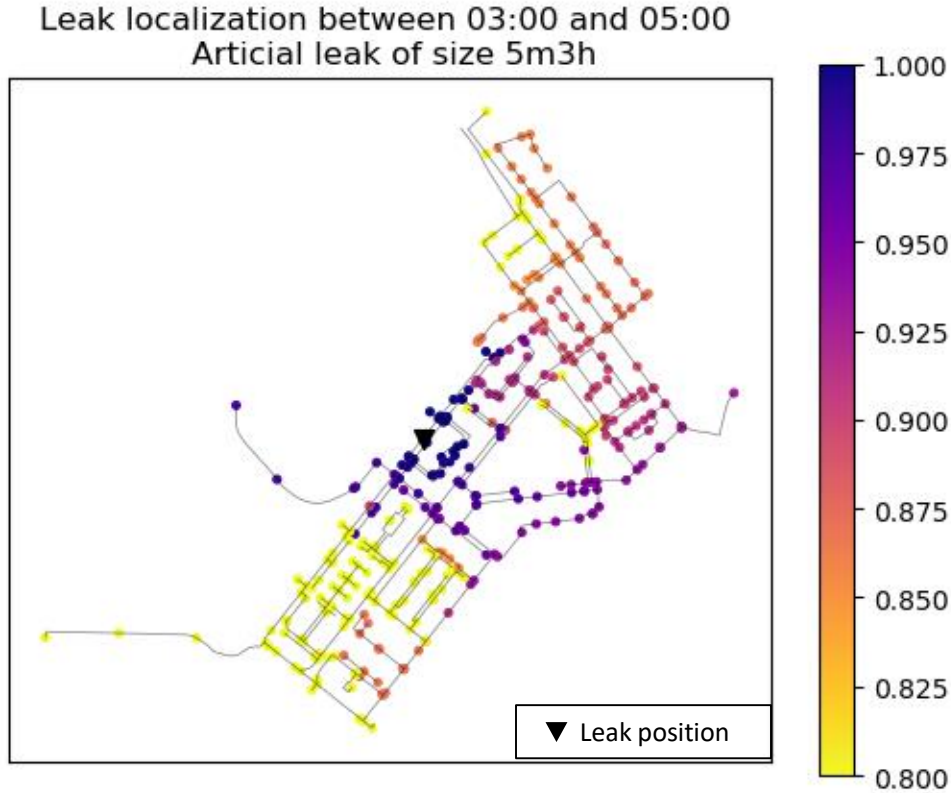


- Get the average detection times of each sensor for 1000 simulations for
 - Starting of a leak at: 03:00, 07:00 and 15:00
- Sensors most sensitive to leaks during the night
 - Low stochastic demand fluctuations, hence easily detected
- Detection time takes on average longer during morning peak for every sensor
 - High stochastic demand fluctuations, hence harder to detect
- Sensor 1 , 4 and 6 are more sensitive to this leak
 - Raise an alarm earlier, on average
 - Are closest to the leak



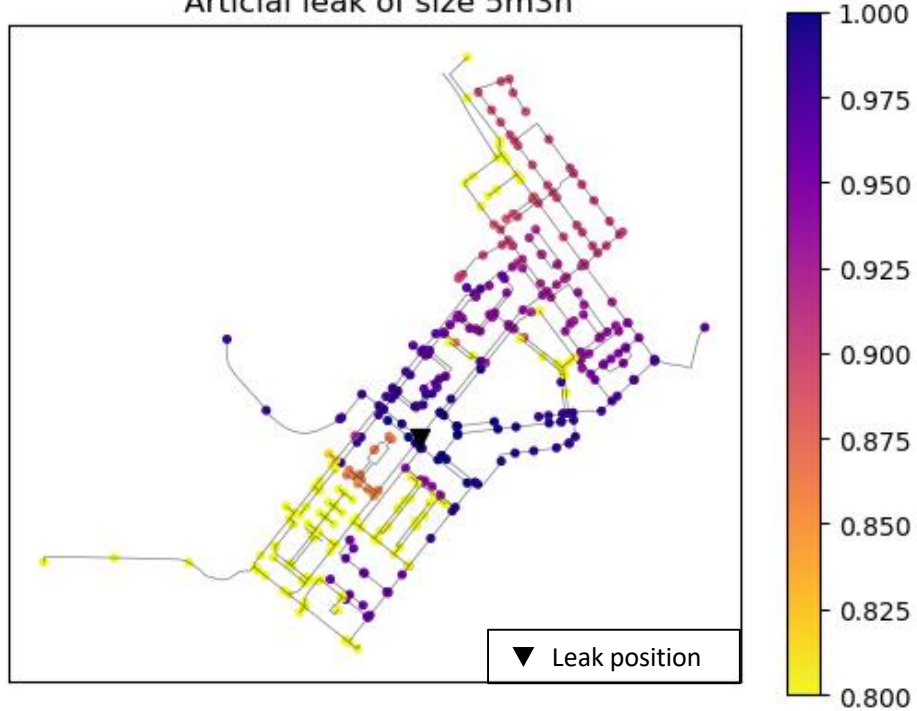
Preliminary results: LEAK LOCALIZATION

- Localization performed for 2 hours, leak discharge 5 m³/h
- Create simulated 'measurements' from single demand simulation and added leak, run simulations of added leak to every node in the network and compare with Pearson's correlation coefficient (colorbar)

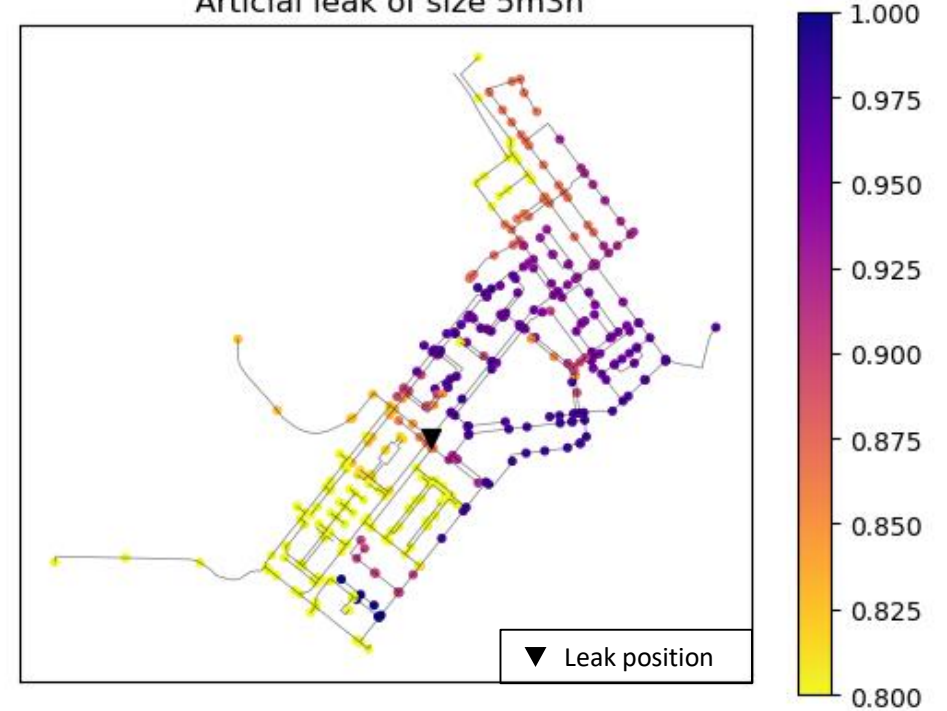


- Change the leak location
- Preliminary result: leak localization performs better during the night (low stochastic demand fluctuations)
 - To do: investigate influence variations stochastic demand on leak localization
 - To do: quantifying the results

Leak localization between 03:00 and 05:00
Artificial leak of size 5m³h



Leak localization between 07:00 and 09:00
Artificial leak of size 5m³h



Conclusion

- Leak detection:
 - A leak is easier to detect at night (low demand fluctuations) and hardest to detect during the morning peak (high demand fluctuations). This holds for the inflow sensor, as well as the pressure sensors
 - The pressure sensors closer to the leak are more sensitive and are able to raise an alarm earlier
- Leak localization:
 - Preliminary results with different leaks show that better performance is achieved during the night (low demand fluctuations)
 - Future steps:
 - Investigate influence variations stochastic demand on leak localization
 - Quantify results of the leak localization

Appendix

Data analysis and calibration hydraulic model

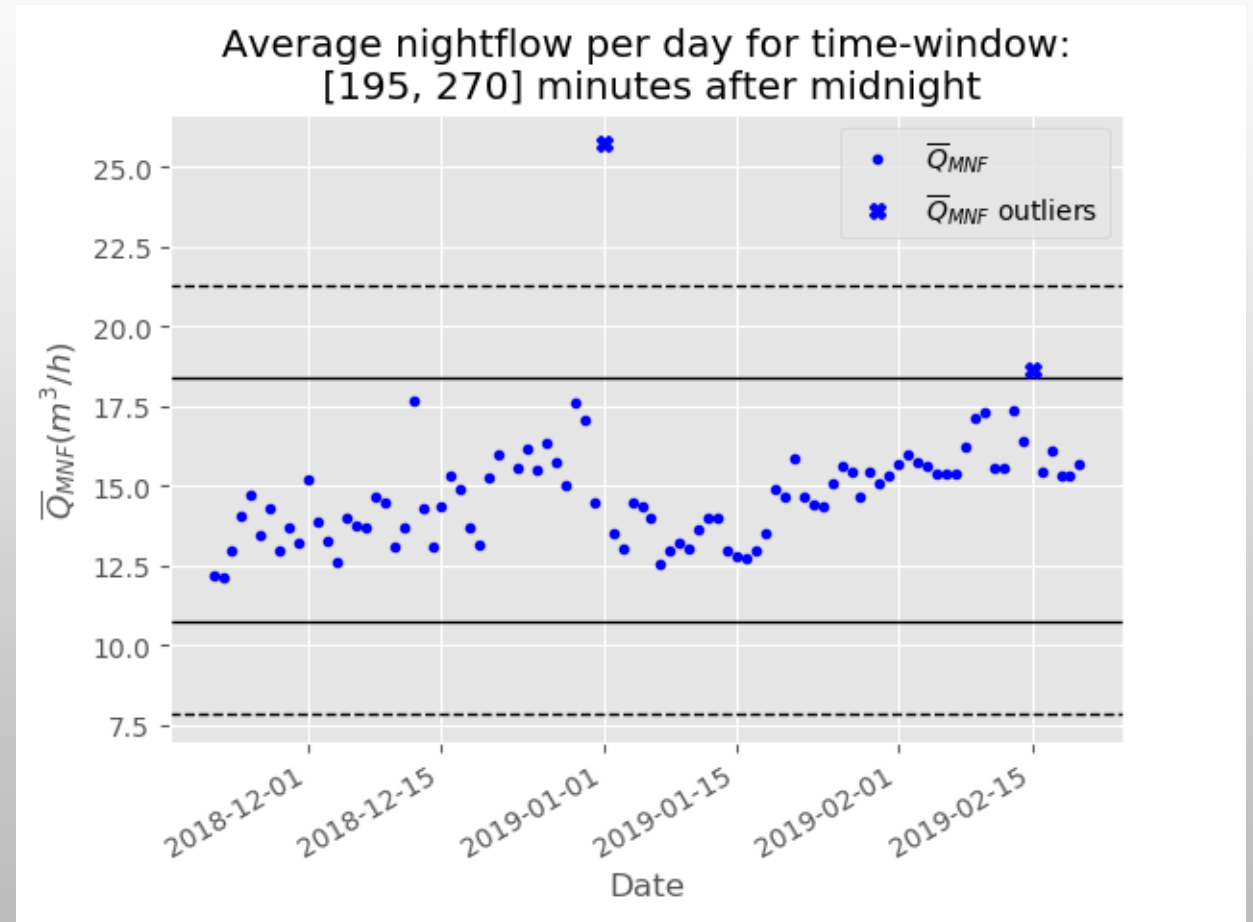
Preparation model: Data analysis

Sensor	Period available data	Data
Pump	2018-10-12 --- 2019-07-16	Discharge
Pump	2019-03-09 --- 2019-07-16	Pressure
Pressure Sensor 5	2018-11-06 --- 2019-03-11	Pressure
Other 5 pressure sensors	2018-11-06 --- 2019-07-15	Pressure

- No long period of overlapping data
- Chosen period for analysis [**2018-nov-21 : 2019-feb-20**]
 - Most stable data
 - Minimal seasonality
 - No data of the pressure at the pump!

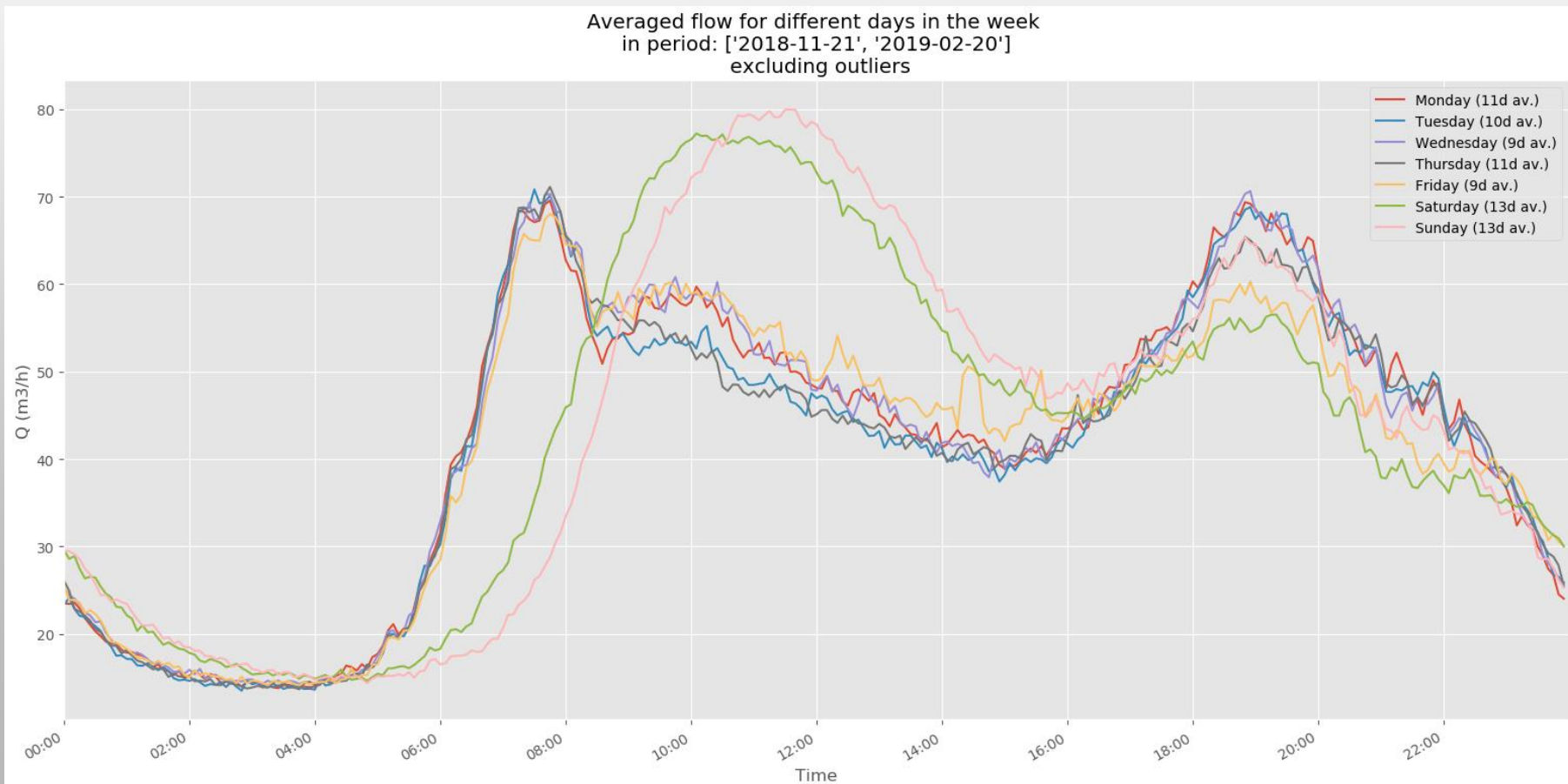
Minimum night-flow analysis

- Night consumption taken between 03:15 – 04:30
 - Flow is lowest in this timeframe for week and weekend nights
- Structural increase in MNF after 17 January
 - Potential leak?



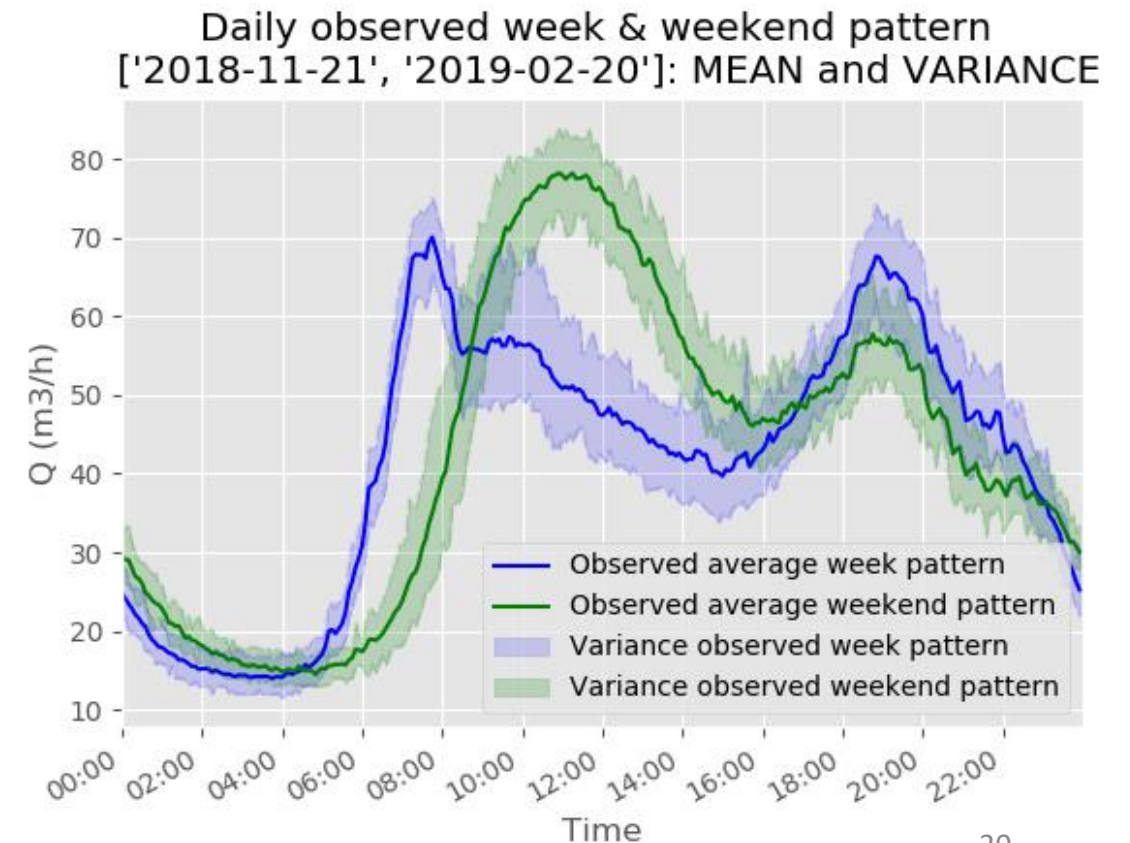
Inflow data at pump

- Plotting the average daily discharge per day of the week (holidays excluded)



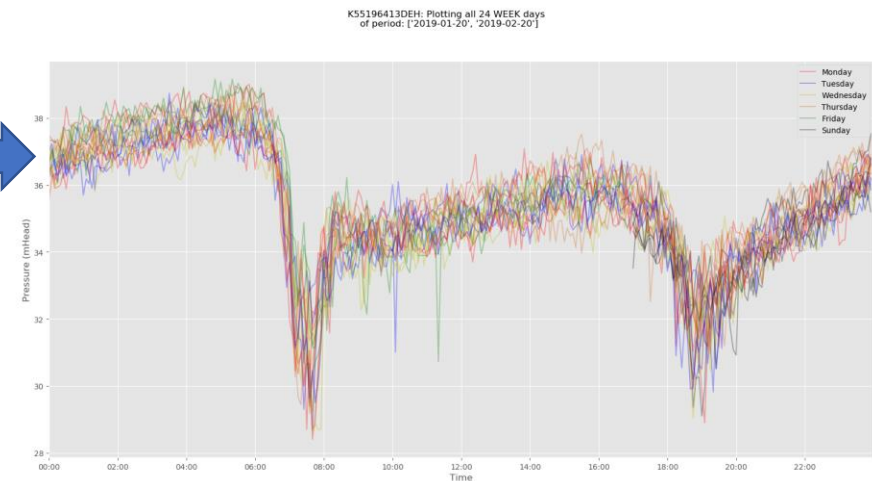
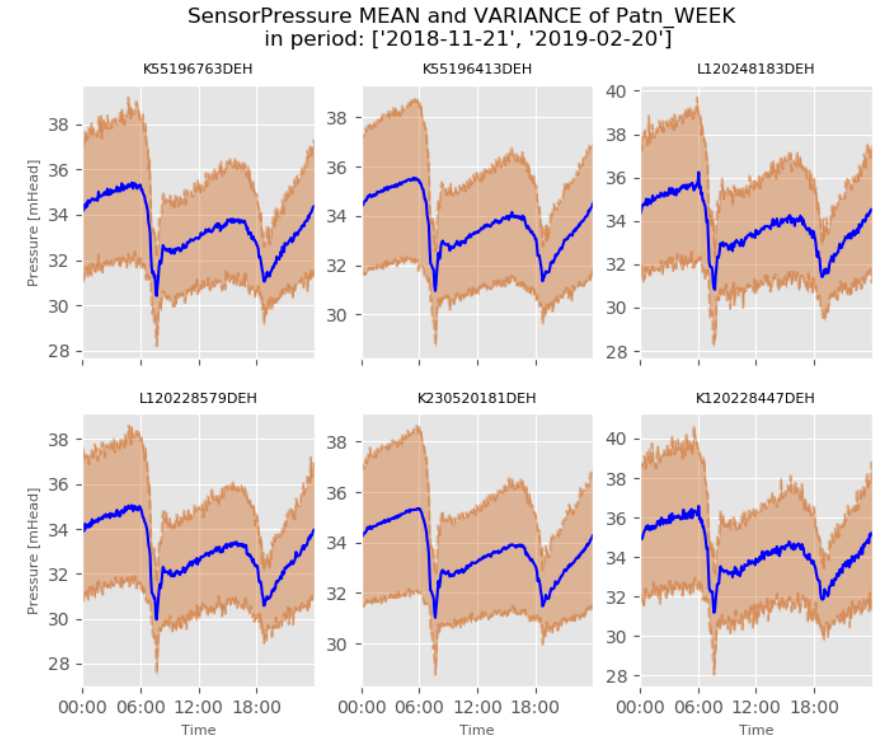
Creating week and weekend patterns

- Creating two categories and corresponding characteristic curves:
 - 1:Week and 2:weekend days
 - Use STL-decomposition to account for structural differences of for example Mondays and Fridays
 - The focus in this study is set on weekdays



Pressure sensor data

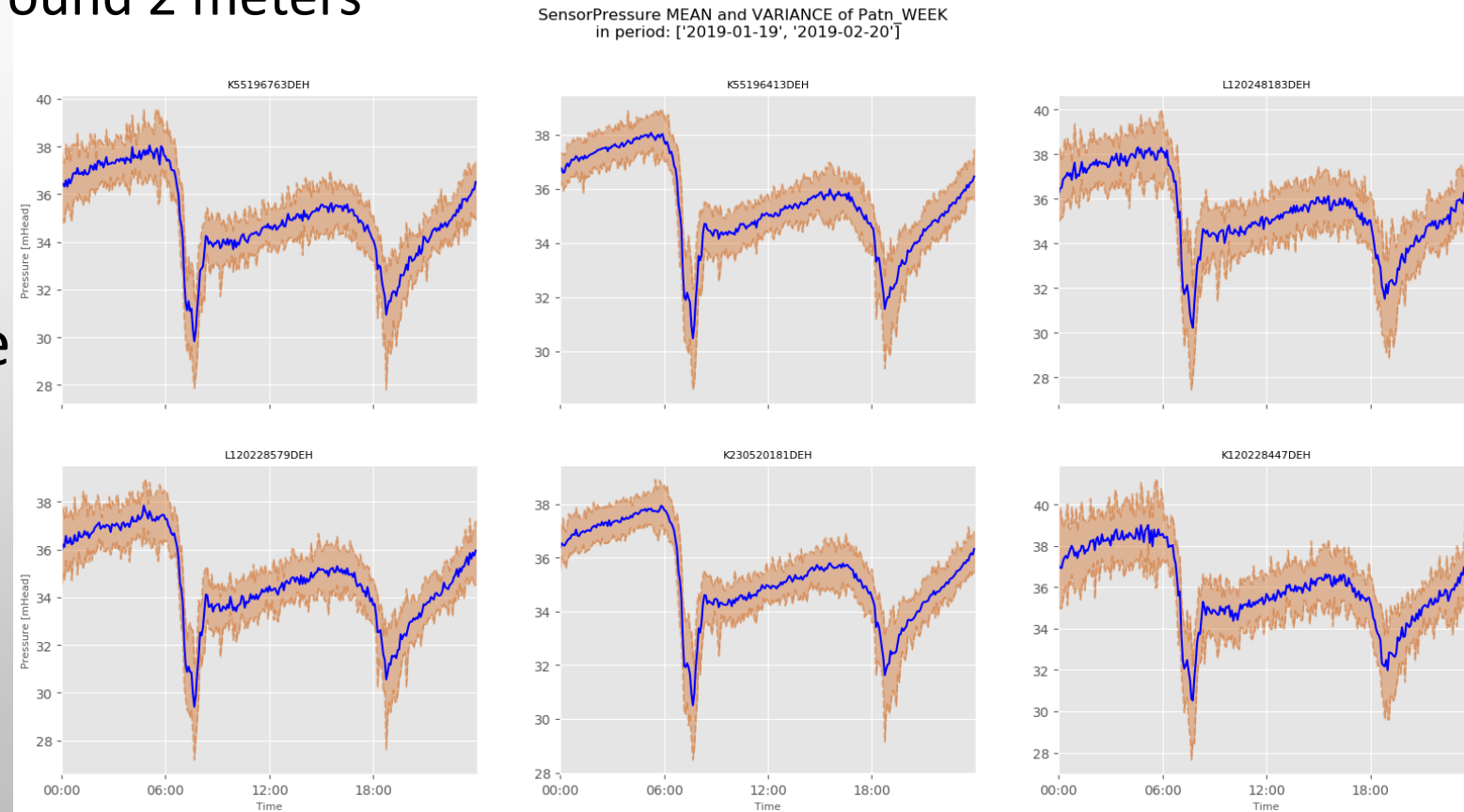
- Huge variances of up to 6 meters chosen time-period!
- Zoom in to one sensor and plotting all the days; shows multiple clusters
 - Different settings in the system
- Take a shorter period: gives one cluster



- For pressure sensor data a shorter period is taken:
 - [2019-jan-19 :: 2019-feb-20]
 - Variability decrease to around 2 meters

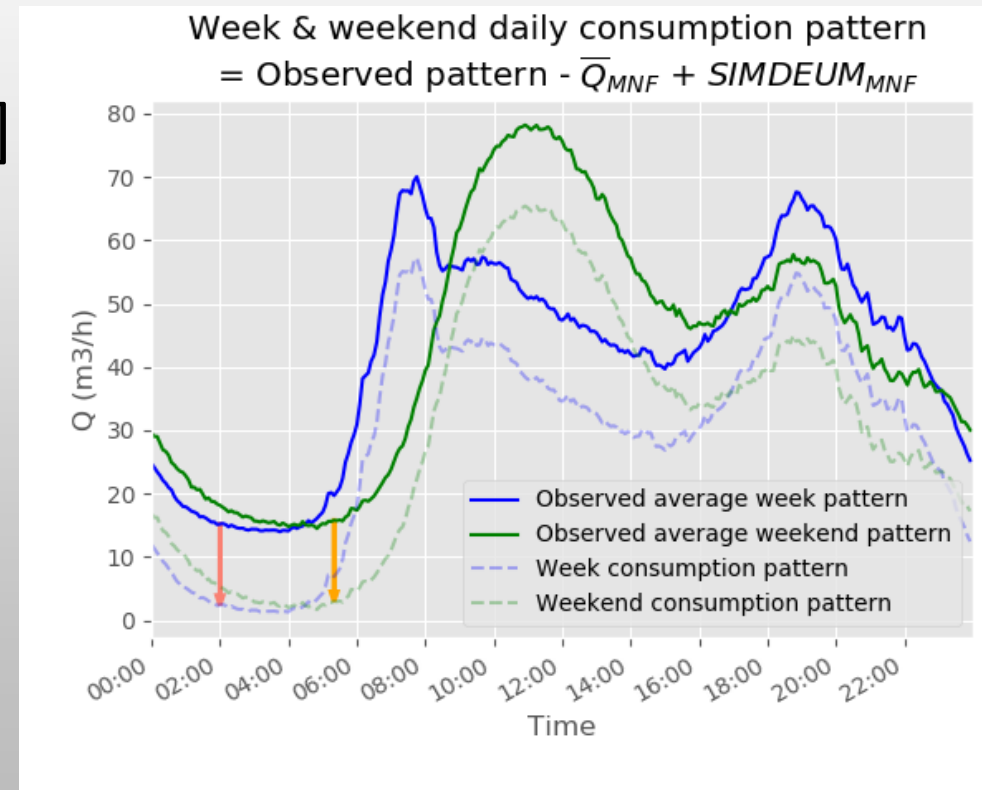
- In all the data there is a structural increase in pressure throughout the night!

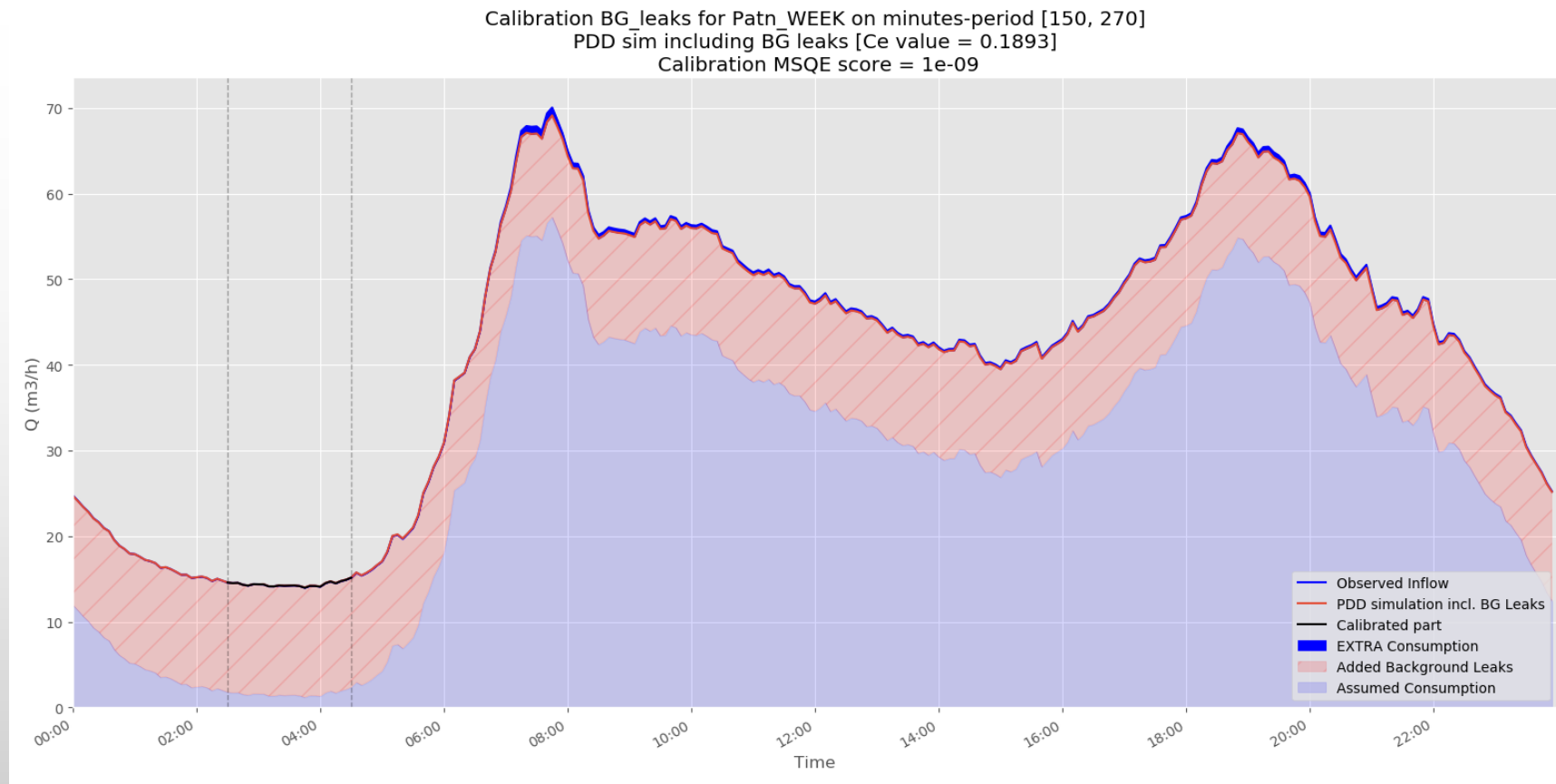
- It turned out to be a wrong setting of the pump booster



Preparation model: Calibration

- The model retrieved from the water utility was outdated, hence a calibration was necessary
- High observed night use! [15 m³/h]
 - Expected consumption based on the amount of households: [2 m³/h]
- Subtract the difference and implement consumption pattern to the model
 - Base demands per node based on billing information implemented
- Implement the rest of the observed Q as background leaks [13 m³/h]



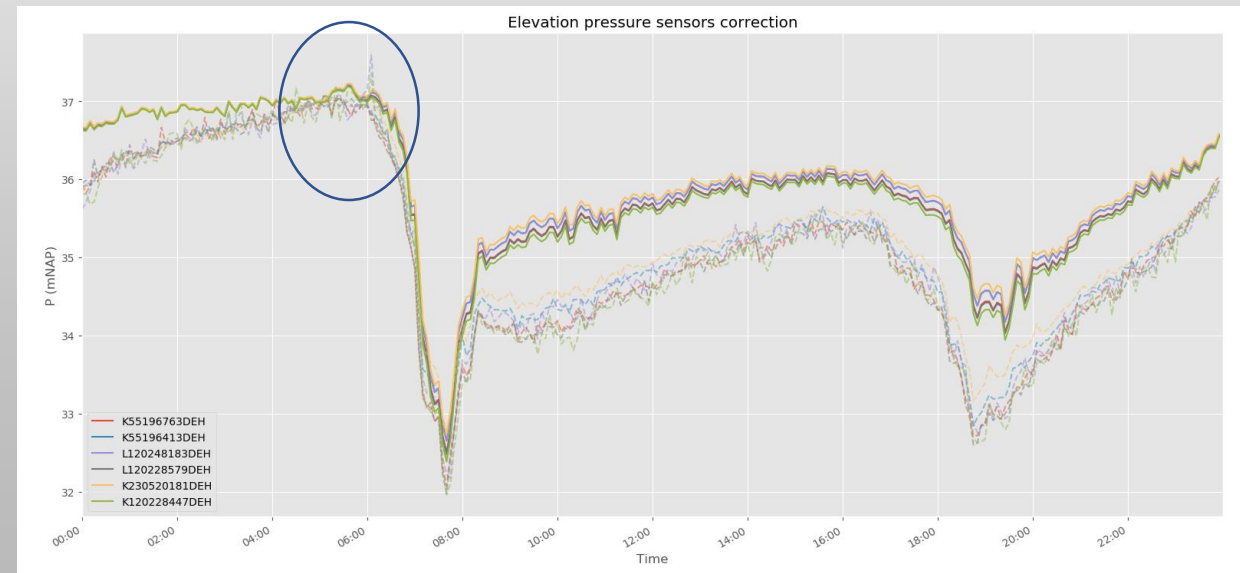
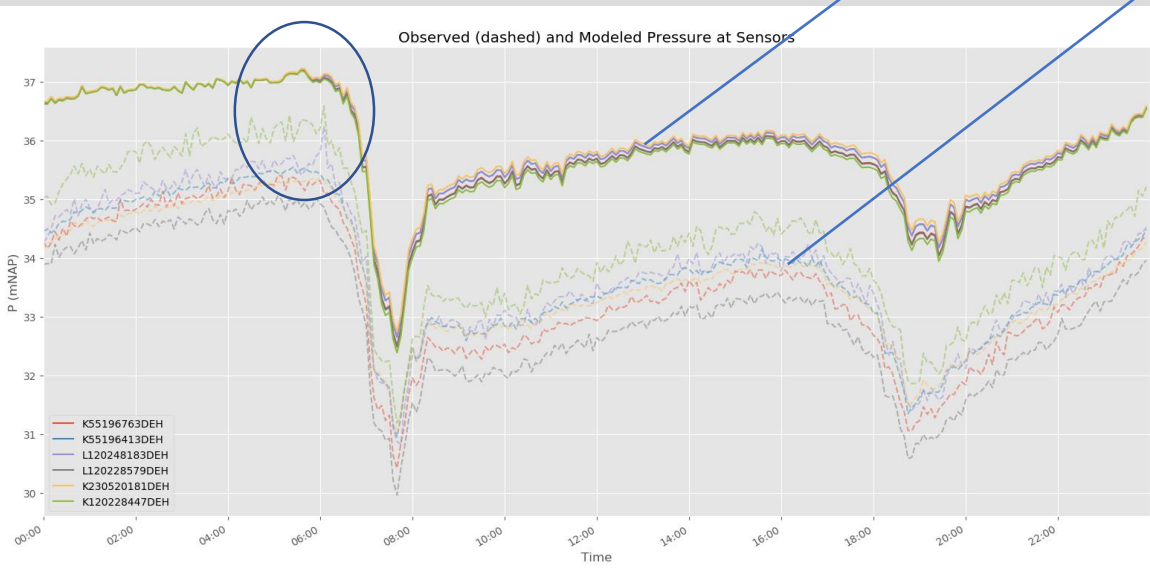


- Using a pressure dependent model: background leak discharges changes throughout day (use of emitters)
- Decrease in background leak discharge during peak hours added to consumption pattern

Calibration: elevation P-sensors correction

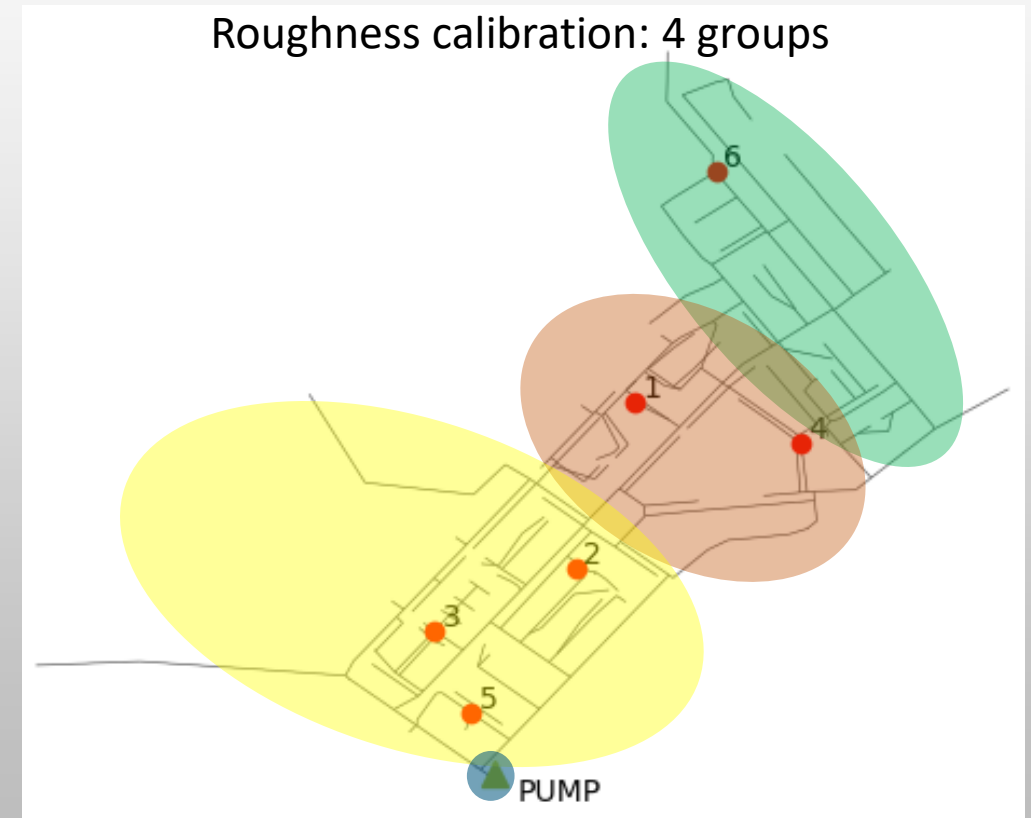
- Correct unknown elevations pressure sensors:
 - During MNF hours: difference in modelled and measured pressure is considered to be the elevation of the sensor
→ corrected in observations with a vertical translation

Modelled pressures Measured pressures



Calibration: Roughness values

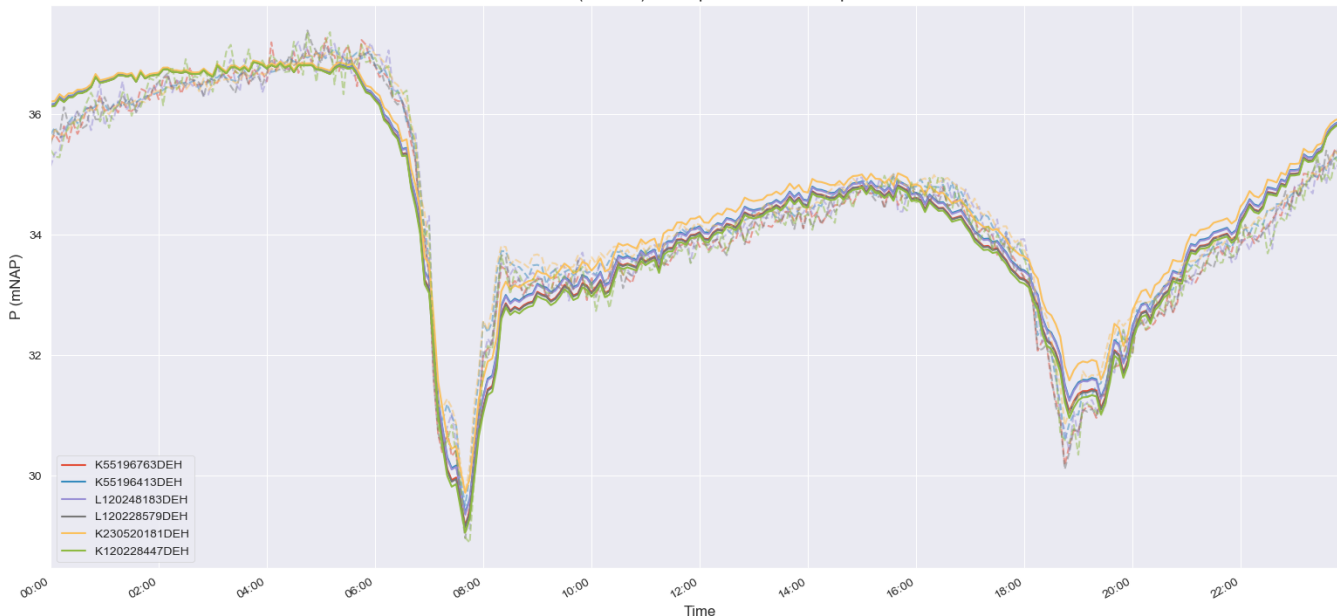
- Group the pipes in four groups by means of distance from the pump
- Give the inflow pipes at the pump a group such that the influence of the pump (and the booster), influencing the entire network, can be accounted for
- Multiply roughness in each group with certain factor and optimize such that:
 $P(\text{model}) \approx P(\text{measured})$



Model calibrated on roughness coefficients

- Observed and modelled pressures now similar, plotting observed-modelled pressures for the 6 pressure sensors (graph to the right)
- Optimized
 - MSQE: 244
 - New H-W roughness coefficients $\in [60,145]$
 - Except for the inflow roughness values (around H-W coeff 10)

Optimized with Roughness Labels with factors: [0.0745, 0.5392, 1.0041, 1.0051], MSQE 243.69
Observed (dashed) and Optimized Modeled pressure



Pressure Residuals (OBS-MOD) at sensors

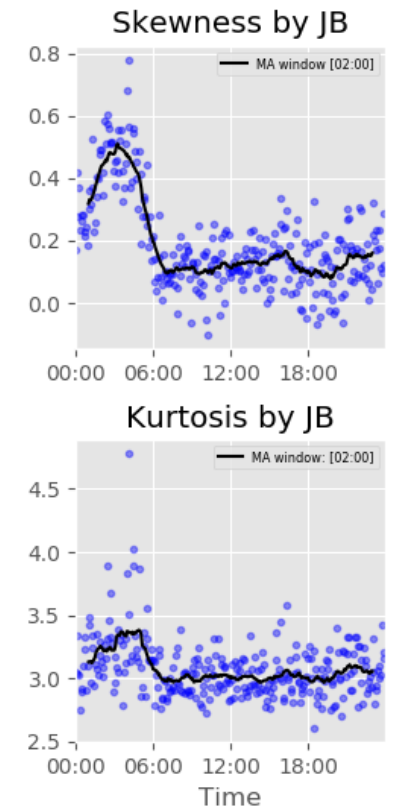
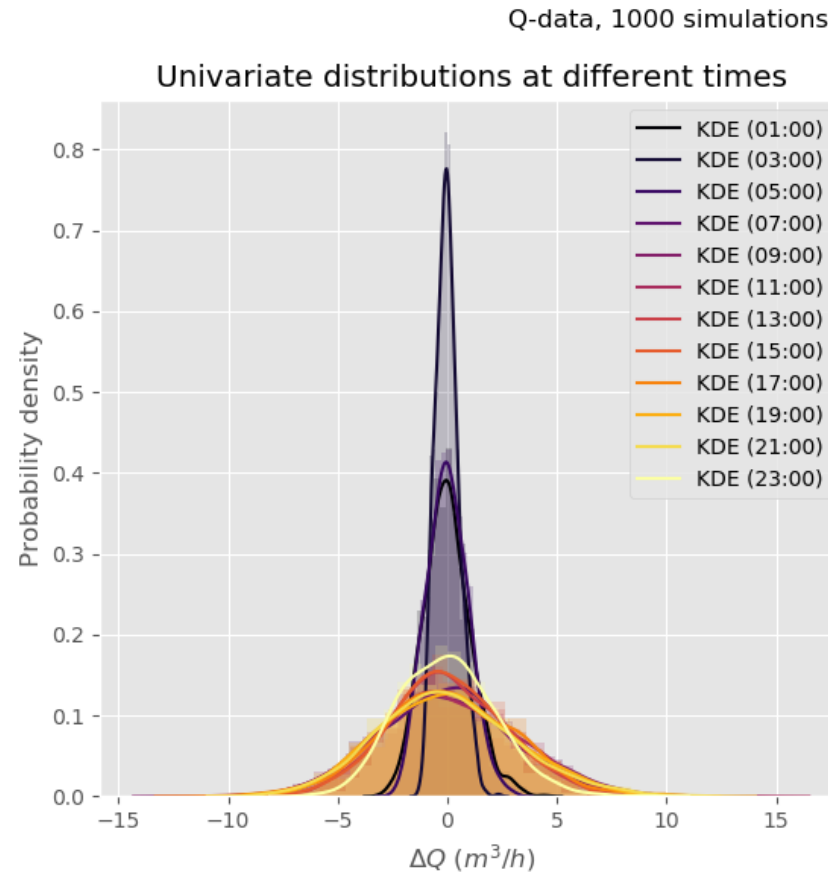


Appendix B

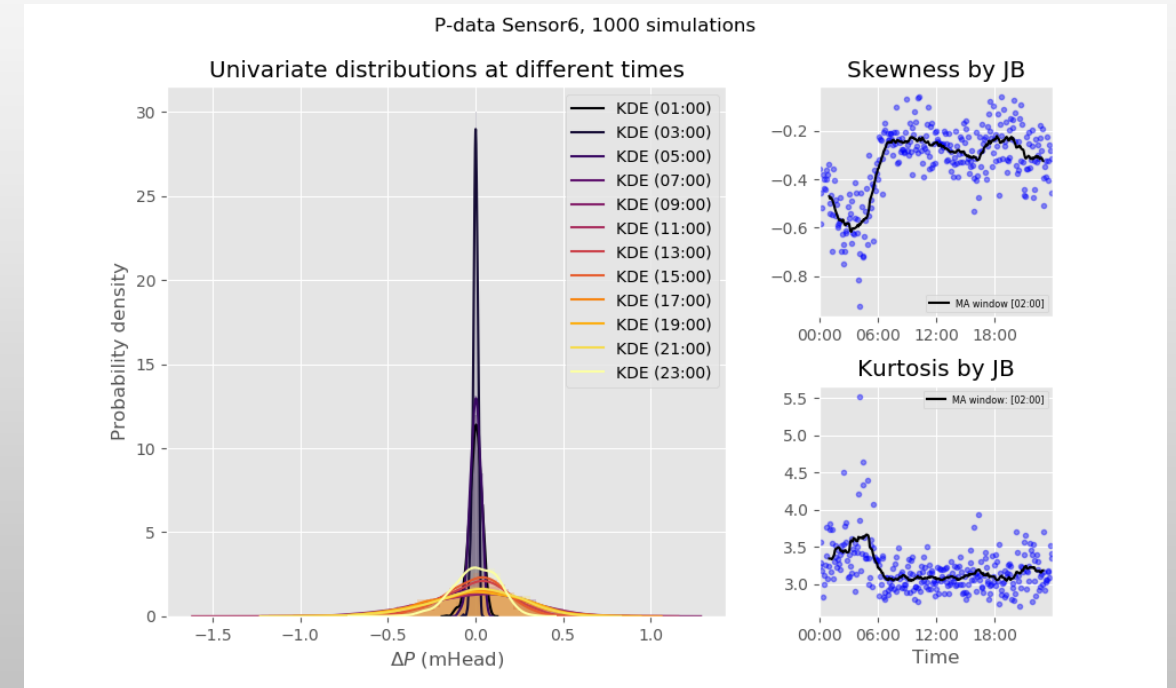
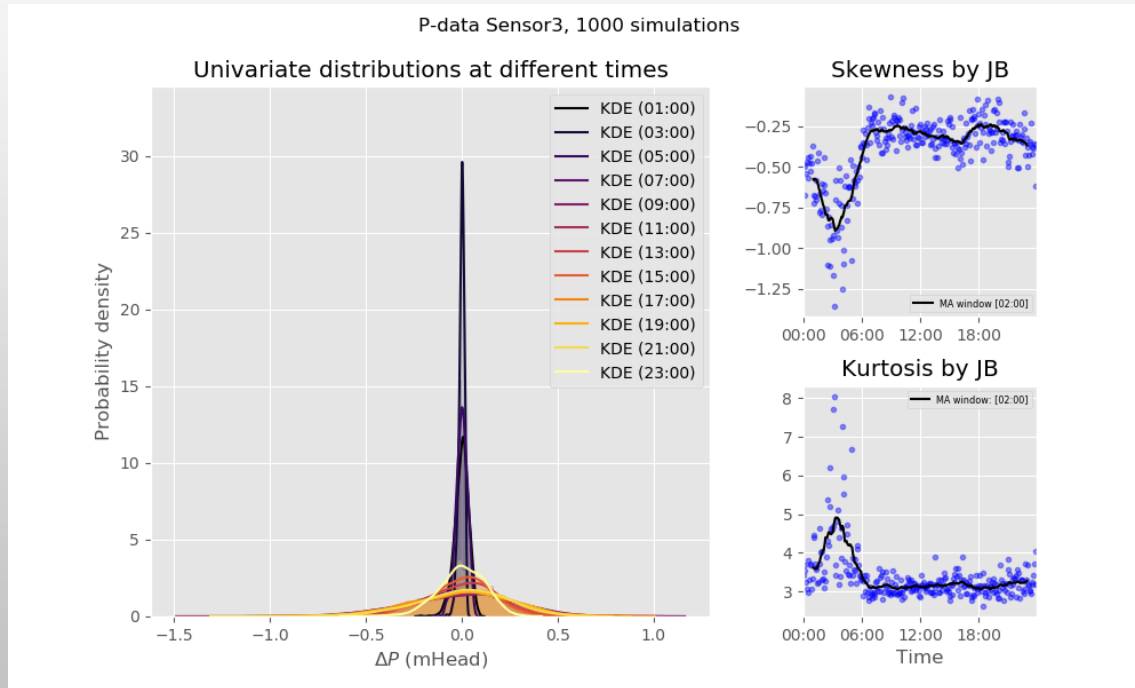
Normality analysis of simulations hydraulic model with coupled stochastic demand model

Simulated Q-data: Gaussian?

- Plotting univariate distributions per timestep
- During the night: distribution is non-normal
- During the day: distribution is relatively fairly normal



Simulated P-data at sensors: Gaussian?



- Generally, all sensors (inflow and pressure sensors) are non-normally distributed throughout the night
- For the inflow sensor, during the day is normally distributed, for the pressure sensors it differs