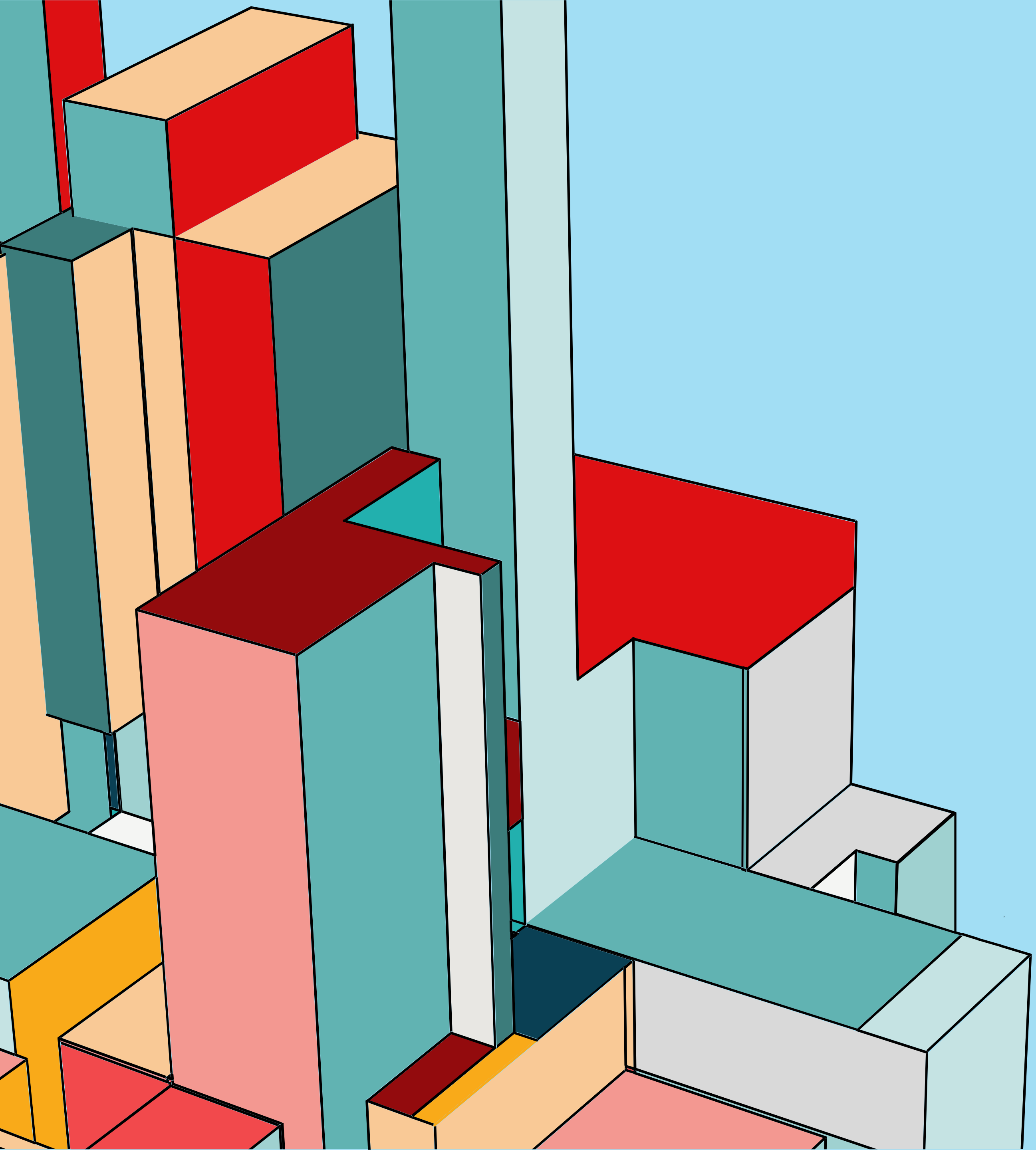


REAL-TIME MONITORING OF BUILDING ENERGY SYSTEMS:

Bayesian Network-based Fault Detection and Diagnosis of an Air-handling Unit in a Dutch University Building

Lars van Koetsveld van Ankeren

October 31st

Brains4Buildings Webinar

PROBLEM STATEMENT

- Buildings account for 40% of European energy consumption [1]

- EU aim: 60% reduction in 2030; fully decarbonised in 2050 [2]

PROBLEM ANALYSIS

- 50% energy to heating, ventilation and air-conditioning (HVAC) systems [3]
- Faults in HVAC systems can cause up to 30% energy waste [4]
- Need for fault detection and diagnosis (FDD) methods
    - Lack of adoption of FDD methods in practice [5]
    - Little research on real-time implementation [5]

RESEARCH AIM

- Real-time diagnosis of air-handling units (AHUs)
- Important part of most HVAC systems
- Large energy consumption within HVAC system [6]

Figure 1: Air-handling unit example

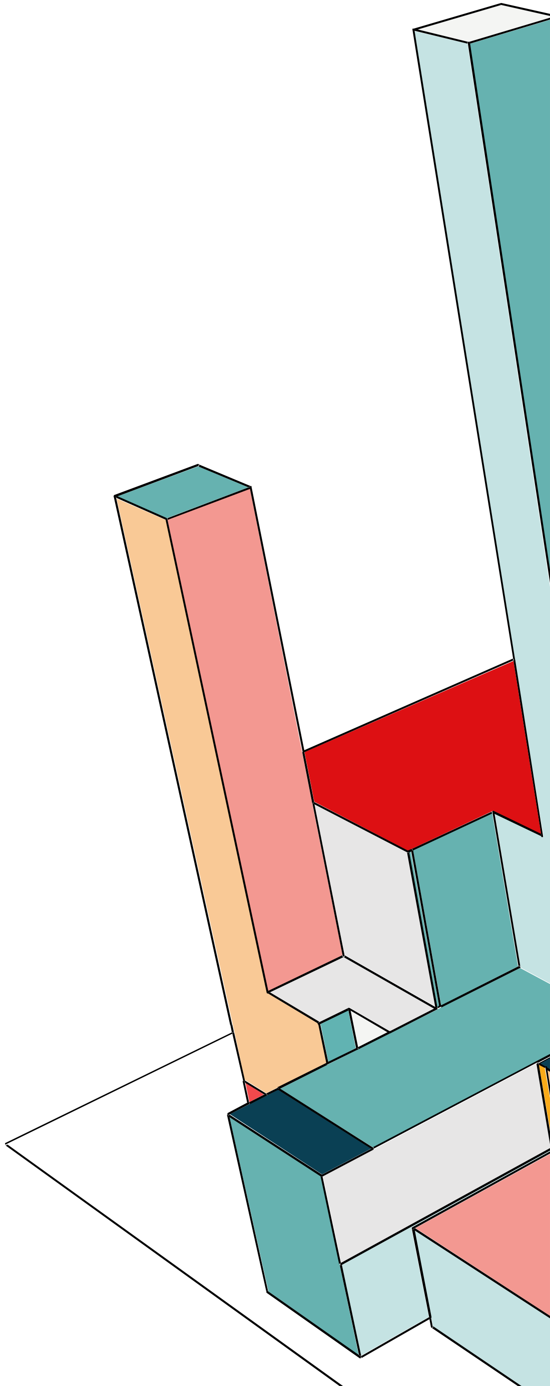
RESEARCH QUESTIONS

- Alternative to data-driven method: Bayesian network-based FDD
    - How to transfer expert knowledge to a probabilistic network?
- Which faults appear frequently in AHUs?
- How can diagnosis be performed in real-time?

RESEARCH QUESTION

‘How can Bayesian network-based fault diagnosis accurately find faults for air-handling units in real-time based on expert knowledge?’

CONTENTS



CASE STUDY DESCRIPTION

- AHU overview
- Scope

AHU OVERVIEW

- Pressure sensors
- Fans
- Temperature sensors
- Heating and cooling coils
- Energy recovery wheel (ERW)

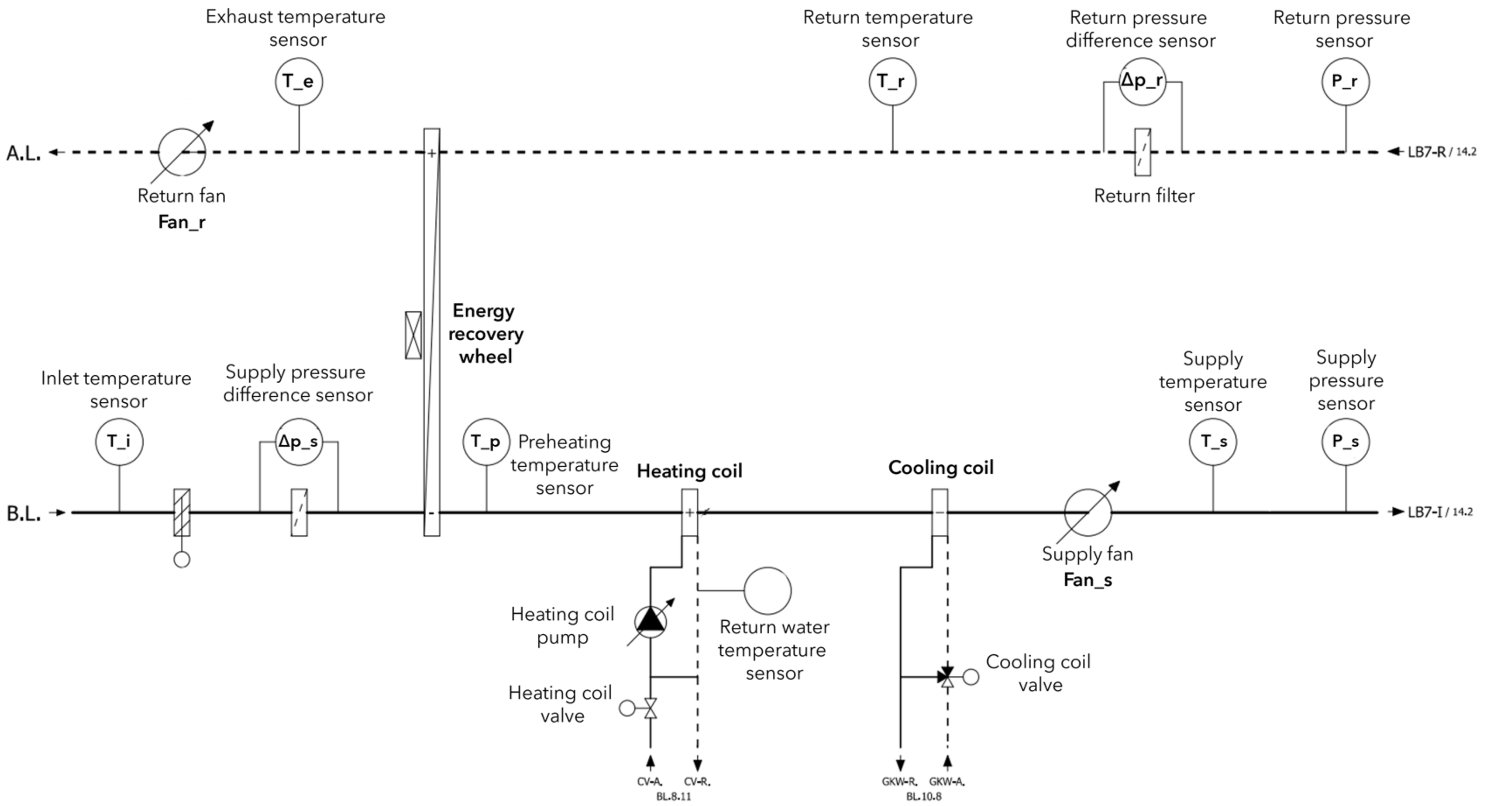


Figure 2: Case study AHU diagram

AHU OVERVIEW

- Pressure setpoints
- Temperature setpoint
- Outdoor temperature
- Alerts

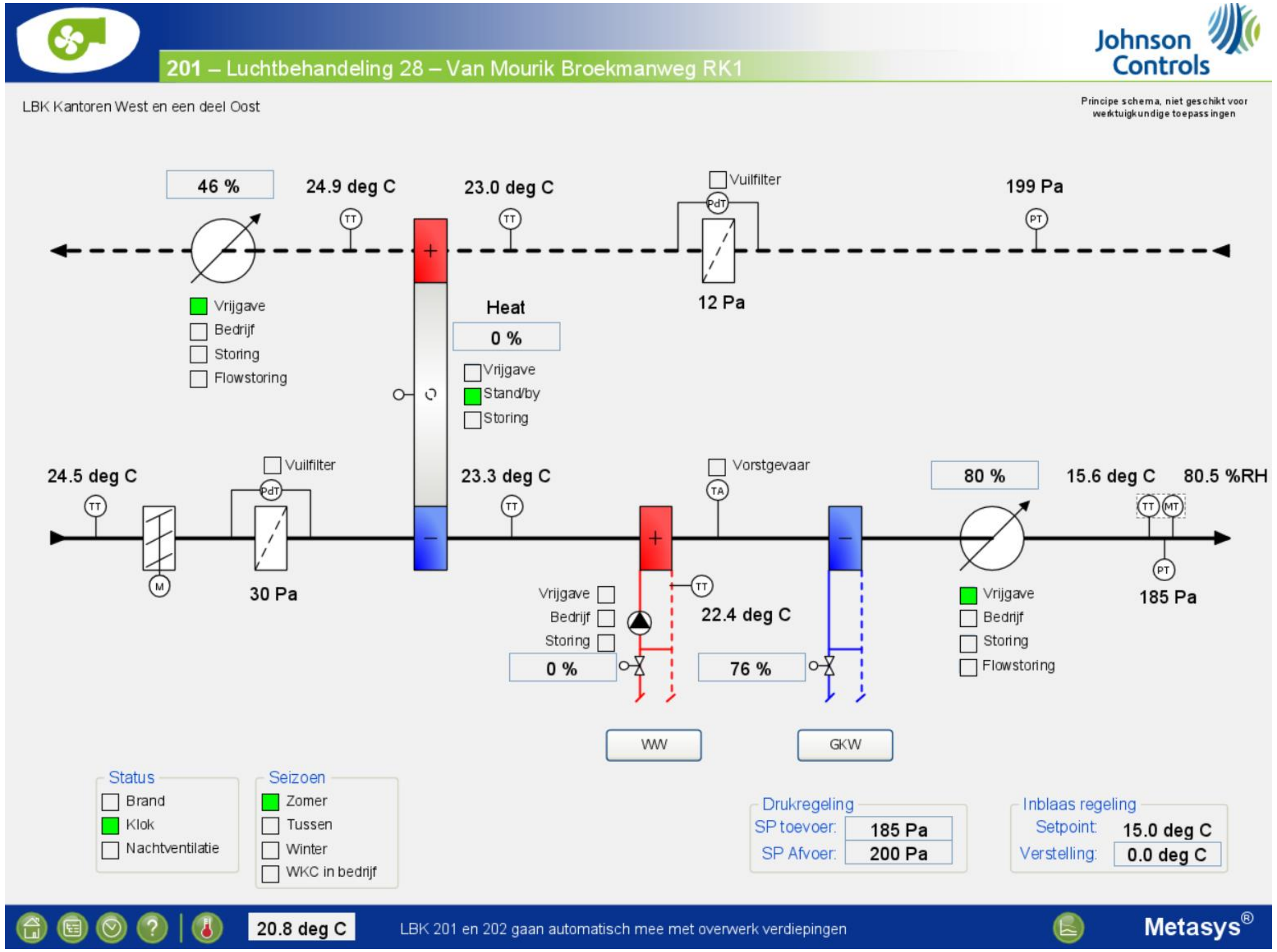


Figure 3: Case study control panel (by Johnson Controls)

SCOPE

- Diagnosis during operation hours
- Focus on winter season, cooling coil not considered

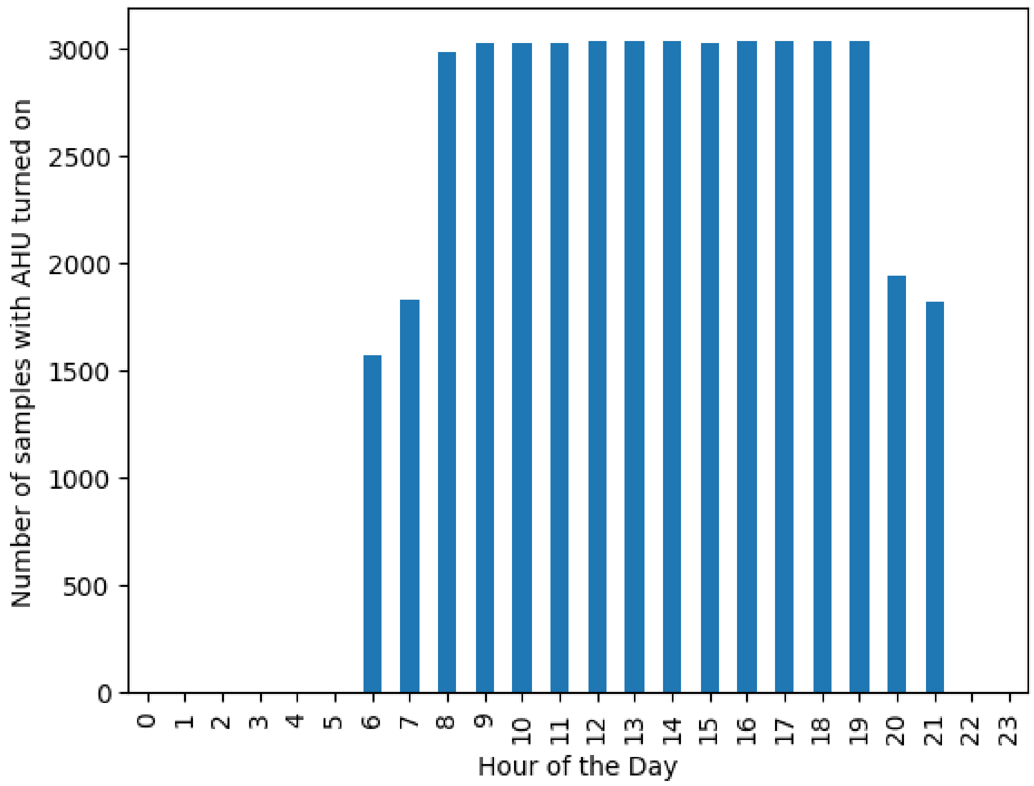


Figure 4: AHU operation schedule

FDD MODEL

- 4S3F framework
- Faults and symptoms
- Diagnostic Bayesian network
- Symptom thresholds

FOUR SYMPTOMS THREE FAULTS (4S3F) FRAMEWORK

- Four symptom types and three fault types
- Separates symptom detection from fault diagnosis [8]
- Fault inference with diagnostic Bayesian network (DBN)

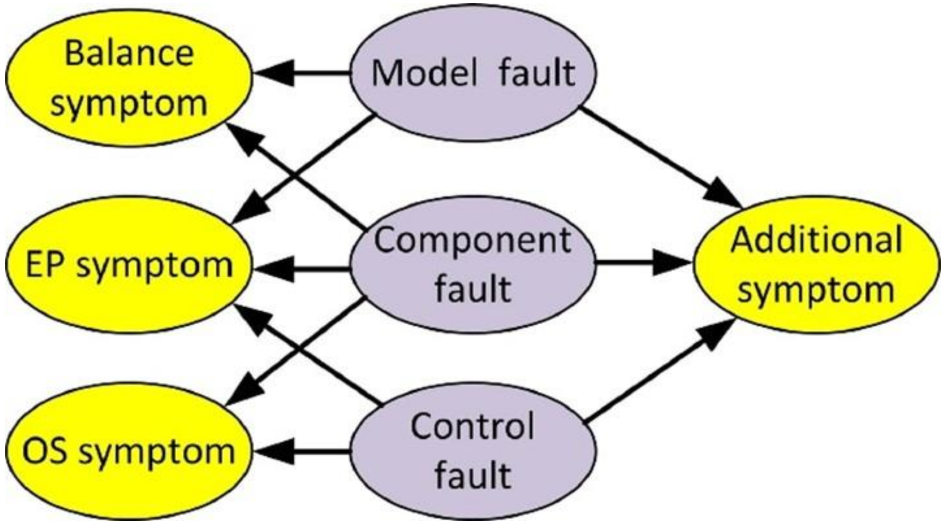


Figure 5: 4S3F framework [7]

DIAGNOSED FAULTS

- 27 AHU faults, based on literature
- Control faults:
  - Incorrect setpoint or control signal
- Component faults:
  - Sensor bias and failure
  - Component failure, leakage or fouling

Component	Fault
Fan_s, fan_r	Failure
$Filter_s$, $filter_r$	Leakage Fouling
Heating coil	Failure Leakage
ERW	Failure
$Damper_s$	Stuck closed
P_s sensor, P_r sensor	Failure
T_i, T_p, T_s, T_{re} combined	Bias
T_i, T_p, T_s, T_r and T_e	Failure

Control	Fault
Temperature setpoint	Setpoint set incorrectly
P_s setpoint, P_r setpoint	Setpoint set incorrectly
ERW control	Incorrect control signal
HCV control	Incorrect control signal
Fan_s control, fan_r control	Incorrect control signal

Figure 6: Diagnosed faults

DETECTED SYMPTOMS

- 35 rule-based symptoms
- Epsilon thresholds determine sensitivities
- Example S1:

  $|T_i - T_o| > \varepsilon_1$

  $\varepsilon_1 = 1\ ^{\circ}C$

	Symptom	Rule
S_1	Comparison T_i and T_o	$\|T_i - T_o\| > \varepsilon_1$
S_2	Supply fan alert is present	$A_{s,fan} = 1$
S_3	Comparison $U_{s,fan}$, $p_{s,set}$ and p_s	$U_{s,fan} < 0\%$ or $U_{s,fan} > 100\%$ or $(U_{s,fan} < 100\%$ and $p_s < p_{s,set} - \varepsilon_2)$ or $(U_{s,fan} > 0\%$ and $p_s > p_{s,set} + \varepsilon_2)$
S_4	Difference $p_{s,set}$ and p_s	$\|p_s - p_{s,set}\| > \varepsilon_3$
S_5	Return fan alert is present	$A_{r,fan} = 1$
S_6	Comparison $U_{r,fan}$, $p_{r,set}$ and p_r	$U_{r,fan} < 0\%$ or $U_{r,fan} > 100\%$ or $(U_{r,fan} < 100\%$ and $p_r < p_{r,set} - \varepsilon_2)$ or $(U_{r,fan} > 0\%$ and $p_r > p_{r,set} + \varepsilon_2)$
S_7	Difference $p_{r,set}$ and p_r	$\|p_r - p_{r,set}\| > \varepsilon_3$
S_8	Comparison $p_{s,set}$	$\|p_{s,set} - 185\| > \varepsilon_4$
S_9	Comparison $p_{r,set}$	$\|p_{r,set} - 200\| > \varepsilon_4$

Figure 7: Several symptom detection rules

DIAGNOSTIC BAYESIAN NETWORK

- Conditional probability parameters
- Top: temperature-related
- Bottom: pressure-related

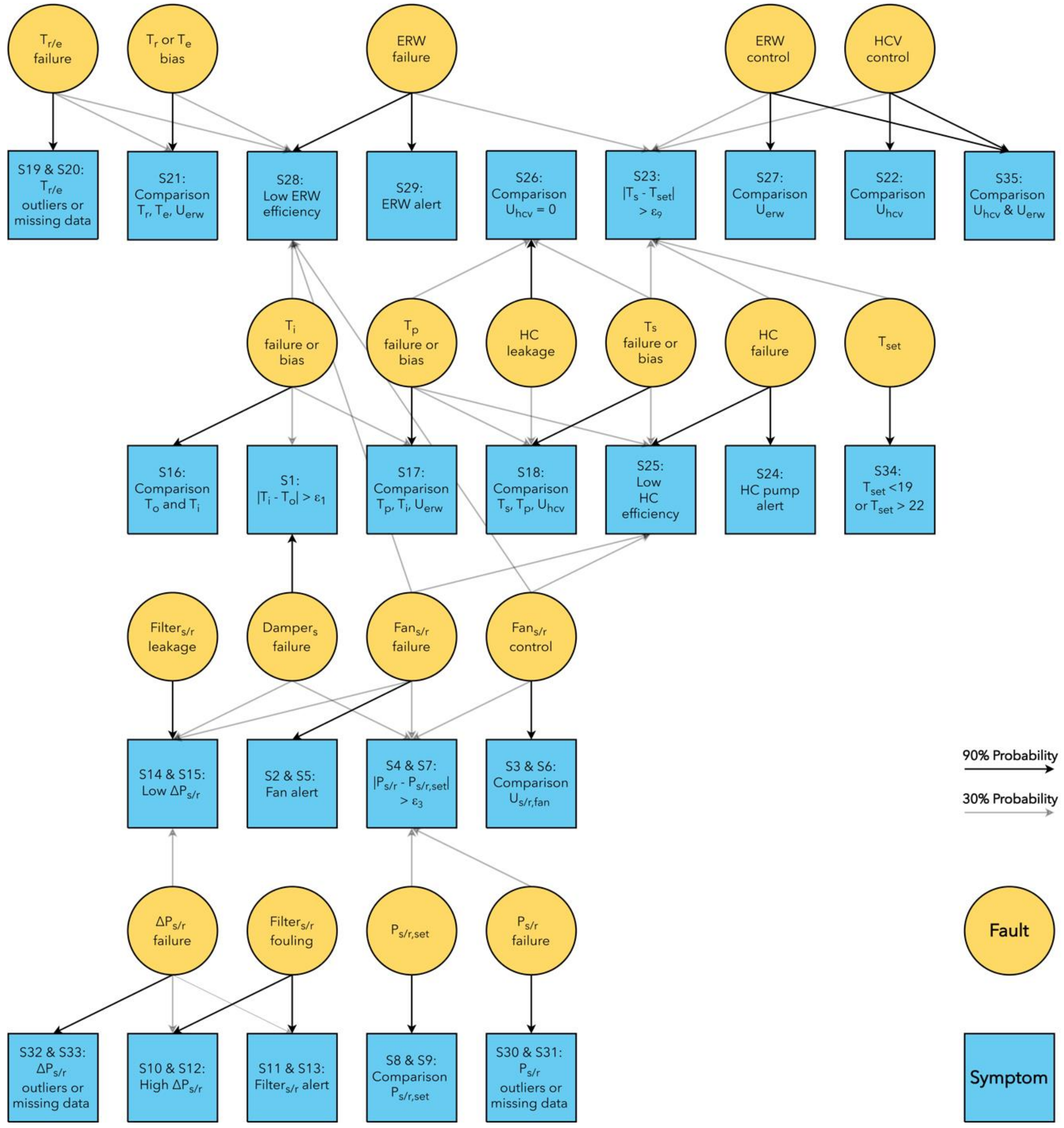


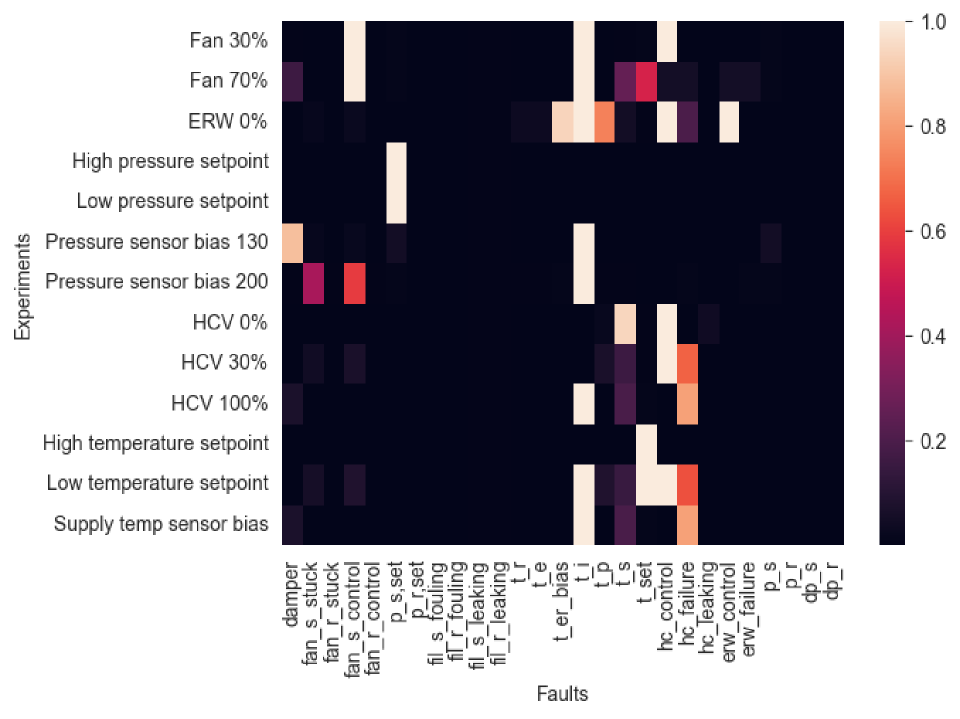
Figure 8: Developed DBN

DIAGNOSIS PARAMETERS

- Configurable diagnosis period: 1-sample up to daily diagnosis
- Symptom thresholds, improving symptom detection accuracy
    - Total number of samples
    - Consecutive number of samples
- Fault diagnosis threshold of 60%

RESULTS

- Experimental
- Historical
- Real-time



EXPERIMENT RESULTS

- Description of experiments
- Detected symptoms
- Diagnosed faults

DESCRIPTION OF EXPERIMENTS

- 13 experiments to validate control and sensor faults
- All conducted in March 2024
- Example: fan control experiment

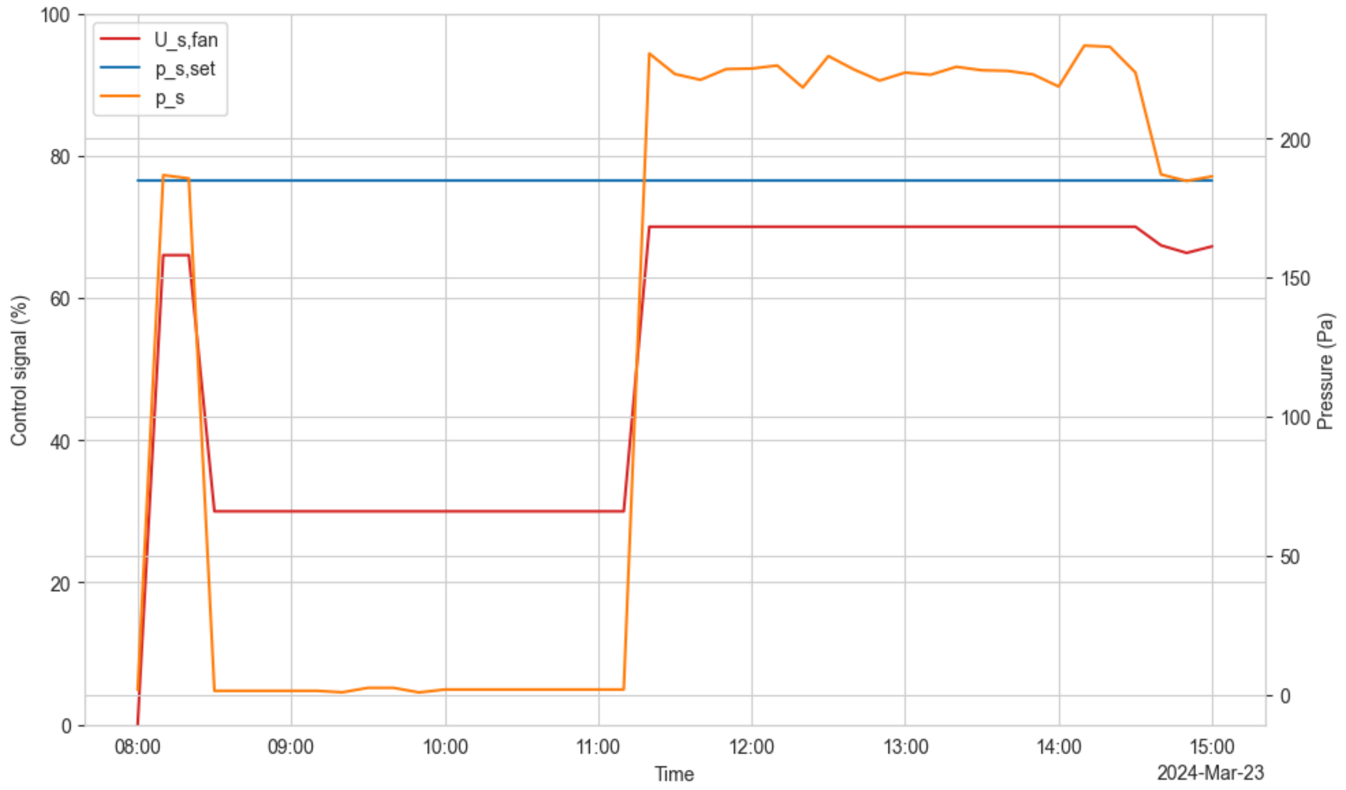


Figure 9: Fan control experiment sensor data

EXPERIMENT RESULTS

- Control faults were diagnosed accurately (9/13)
- Pressure sensor fault not included (2/13)
- HC failure during HCV experiment (1/13)
- DBN could not distinguish between supply temperature sensor and HC failure faults (1/13)

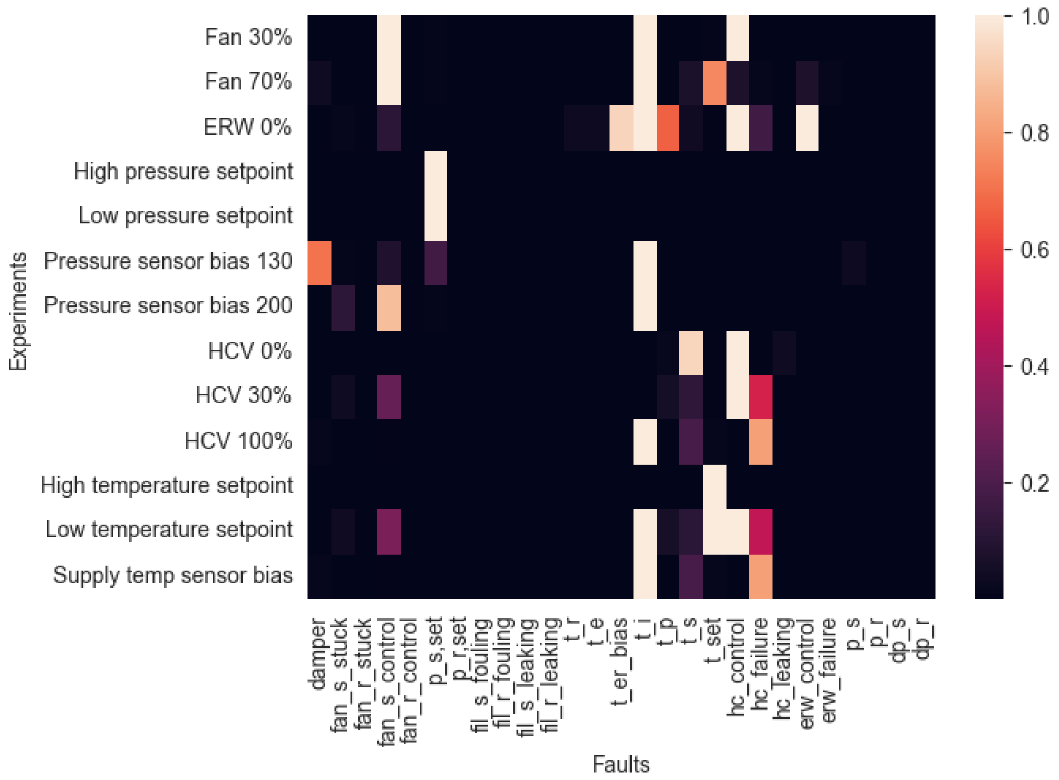


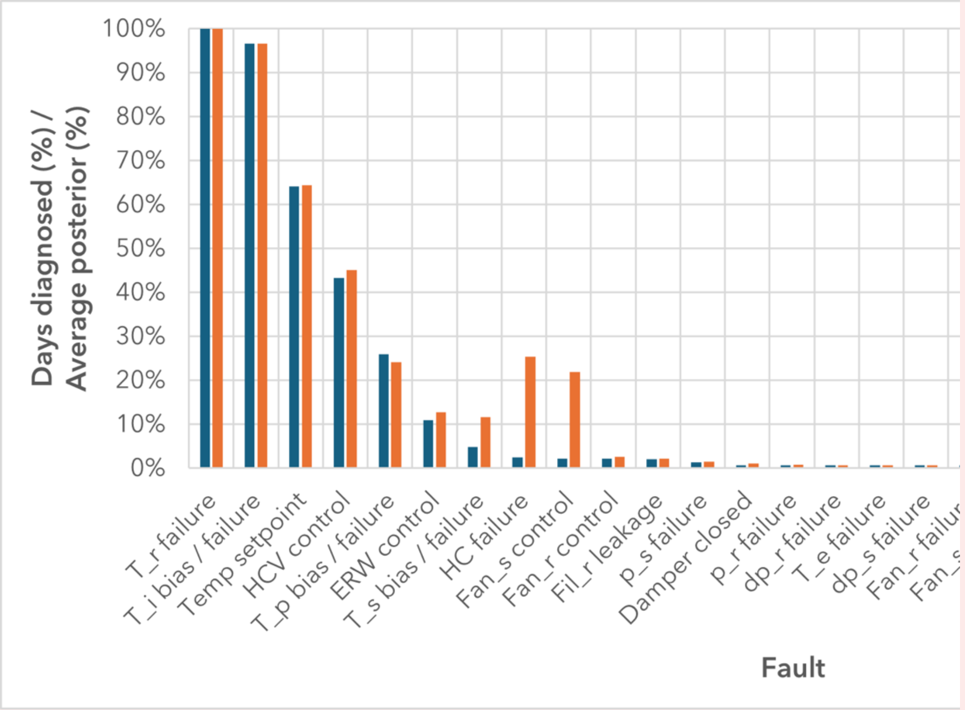
Figure 10: Calculated fault probabilities for each experiment

EXPERIMENT DIAGNOSIS PERIODS

- Five diagnosis periods
- Diagnosis period affected number of false positives
- Trade-off between accuracy and early diagnosis

Diagnosis period Fault	10 minutes	30 minutes	1 hour	2 hours	3 hours
$U_{s,fan}$ = 30%	$U_{s,fan}$, T_{er} bias, T_i, T_s	$U_{s,fan}$, T_{er} bias, T_i	$U_{s,fan}$, T_{er} bias, T_i, U_{hcv}	$U_{s,fan}$, T_{er} bias, T_i, U_{hcv}	$U_{s,fan}$, T_i, U_{hcv}
$U_{s,fan}$ = 70%	$U_{s,fan}$, U_{hcv}	$U_{s,fan}$, U_{hcv}	$U_{s,fan}$, T_i, U_{hcv}	$U_{s,fan}$, T_i	$U_{s,fan}$, T_i
U_{erw} = 0%	T_{er} bias, T_p	T_{er} bias, T_p	T_{er} bias, T_p	T_{er} bias, T_i, T_p	T_{er} bias, T_i, T_p
$p_{s,set}$ = 235 Pa	$p_{s,set}$	$p_{s,set}$	$p_{s,set}$	$p_{s,set}$, U_{hcv}	$p_{s,set}$
$p_{s,set}$ = 135 Pa	$U_{s,fan}$, $p_{s,set}$, T_i	$p_{s,set}$, T_i	$p_{s,set}$, T_i	$p_{s,set}$	$p_{s,set}$
p_s = 130 Pa	$U_{s,fan}$, $U_{r,fan}$, T_i, U_{hcv}	$Damper_s$, T_i	$Damper_s$, T_i	$Damper_s$, T_i	$Damper_s$, T_i
p_s = 200 Pa	$U_{s,fan}$, U_{hcv}	$U_{s,fan}$, U_{hcv}	$U_{s,fan}$, T_i, U_{hcv}	$U_{s,fan}$, T_i, U_{hcv}	$U_{s,fan}$, T_i, U_{hcv}
U_{hcv} = 0%	T_s, U_{hcv}	T_s, U_{hcv}	T_s, U_{hcv}	T_s, U_{hcv}	T_s, U_{hcv}
U_{hcv} = 30%	U_{hcv}	U_{hcv}	U_{hcv}	U_{hcv}	U_{hcv}
U_{hcv} = 100%	T_i, HC	T_i, HC	T_i, HC	T_i, HC	T_i, HC
T_{set} = 23 °C	T_{set}	T_{set}	T_{set}, U_{hcv}	T_{set}	T_{set}
T_{set} = 17 °C	T_{er} bias, T_p, T_{set}	T_{set}, U_{hcv}	T_{set}, U_{hcv}	T_{set}, U_{hcv}	T_i, T_{set}, U_{hcv}
T_s = 17 °C	T_i, U_{hcv}	T_i, U_{hcv}	T_i, U_{hcv}	T_i, U_{hcv}	T_i, HC

Figure 11: Diagnosed faults with different diagnosis periods



HISTORICAL RESULTS

- Detected symptoms
- Diagnosed faults

DETECTED SYMPTOMS

- Model was run on 506 days from 2022 and 2023, between 08:00 and 20:00
- Symptom thresholds: total = 3; consecutive = 2
- Eleven symptoms detected frequently

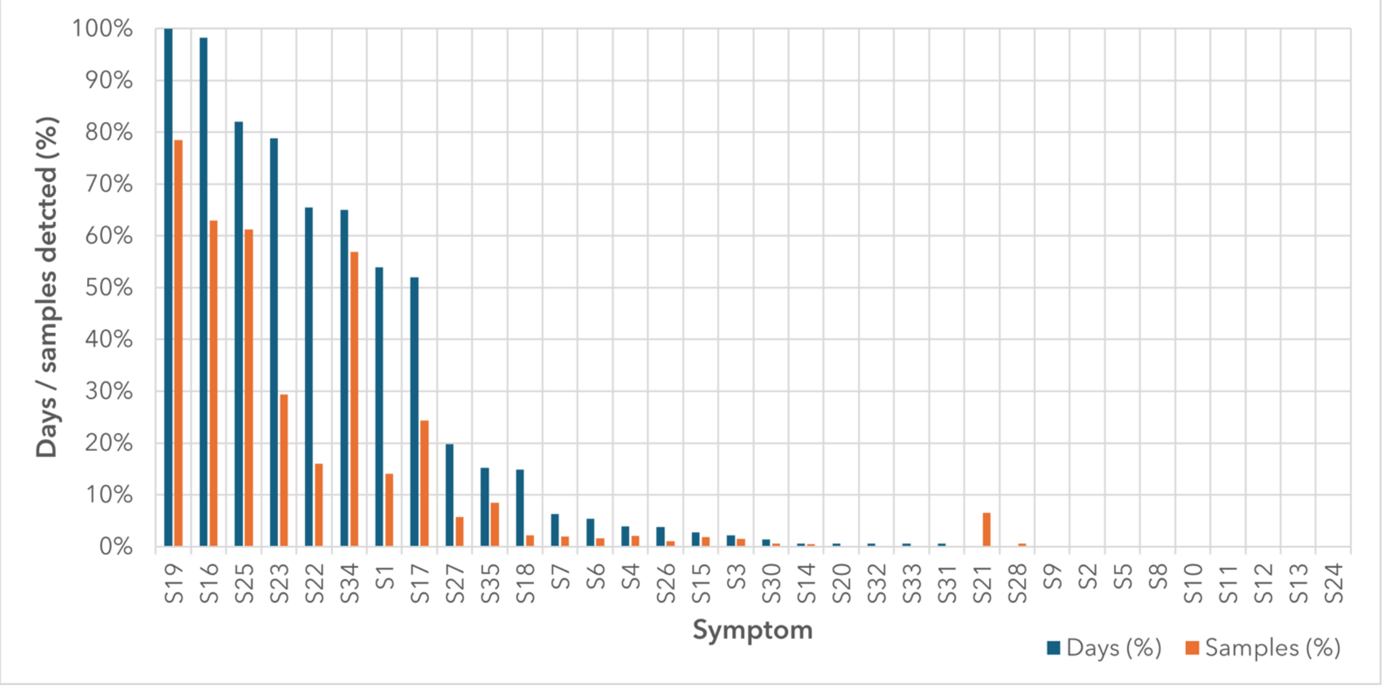


Figure 12: Detected symptoms in historical data

DIAGNOSED FAULTS

- Seven temperature-related faults diagnosed frequently
- Mostly control faults
- Biases detected often

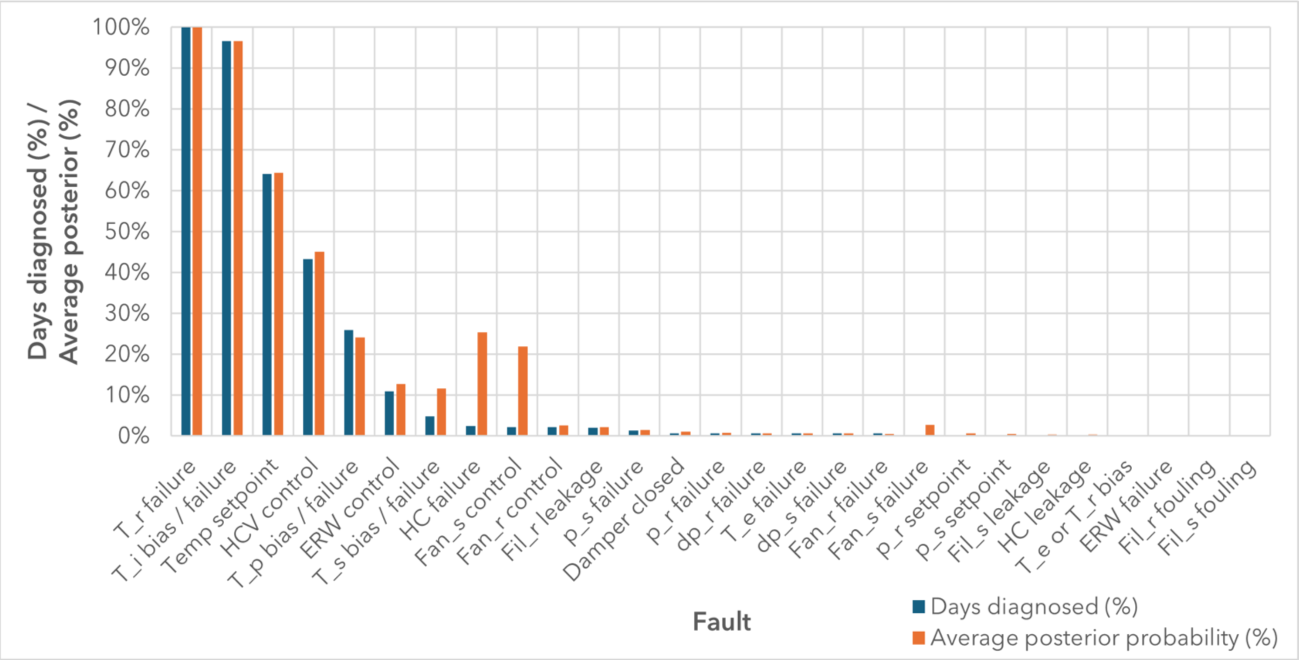


Figure 13: Diagnosed faults in historical data

DIAGNOSED FAULTS

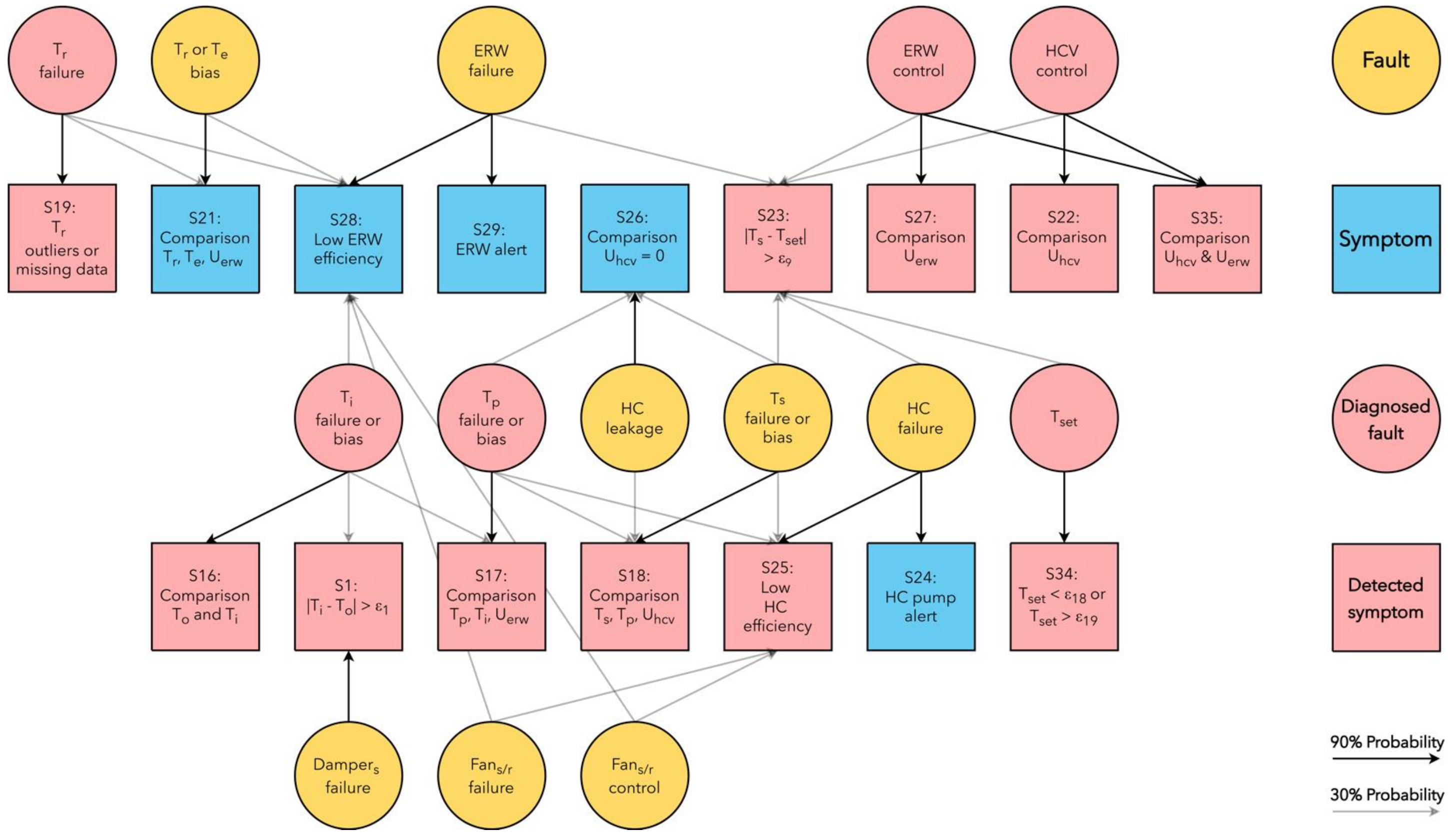
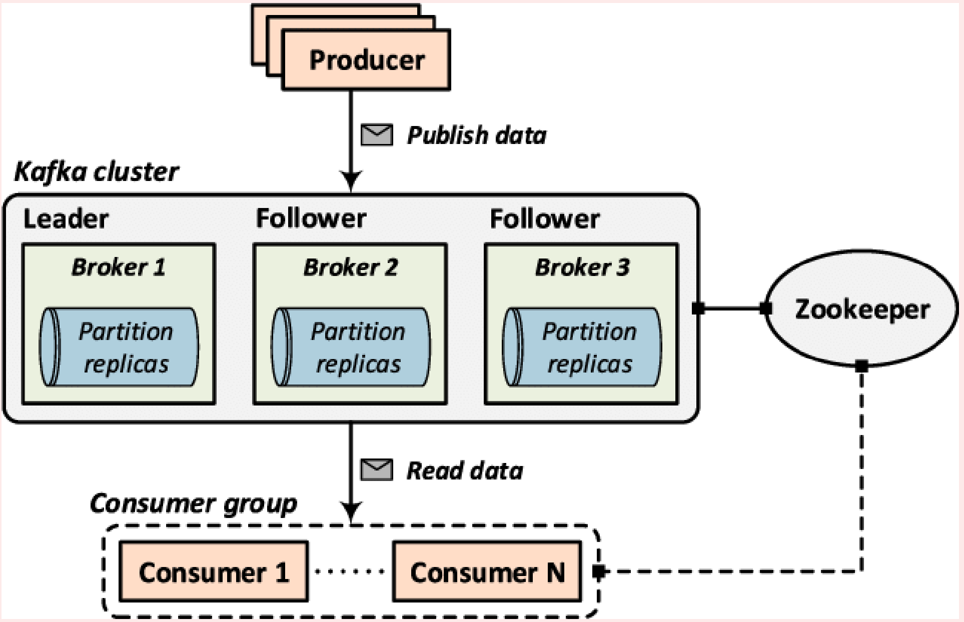


Figure 14: Symptoms and faults diagnosed (>10%), shown in DBN



REAL-TIME RESULTS

- Real-time diagnosis framework
- Diagnosis setup
- Diagnosis results

REAL-TIME DIAGNOSIS FRAMEWORK

- Data streaming software Kafka used to collect real-time data
- Stored locally in time-series database InfluxDB
- DBN performs diagnosis on configurable period

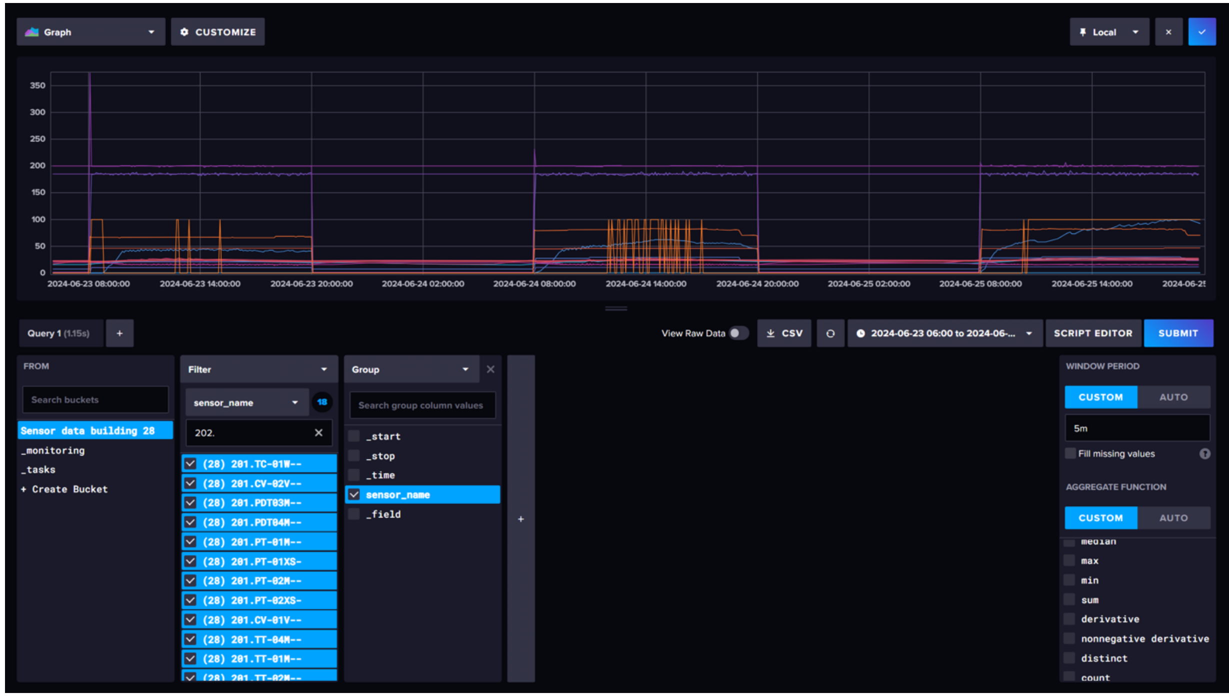


Figure 15: InfluxDB UI

DIAGNOSIS SETUP

- Data collected between the 21st and 25^{th} of June 2024
- Diagnosis on data from 08:00 until 20:00 on the 24^{th} of June
- Symptom thresholds equal to setup for historical results

DIAGNOSIS RESULTS

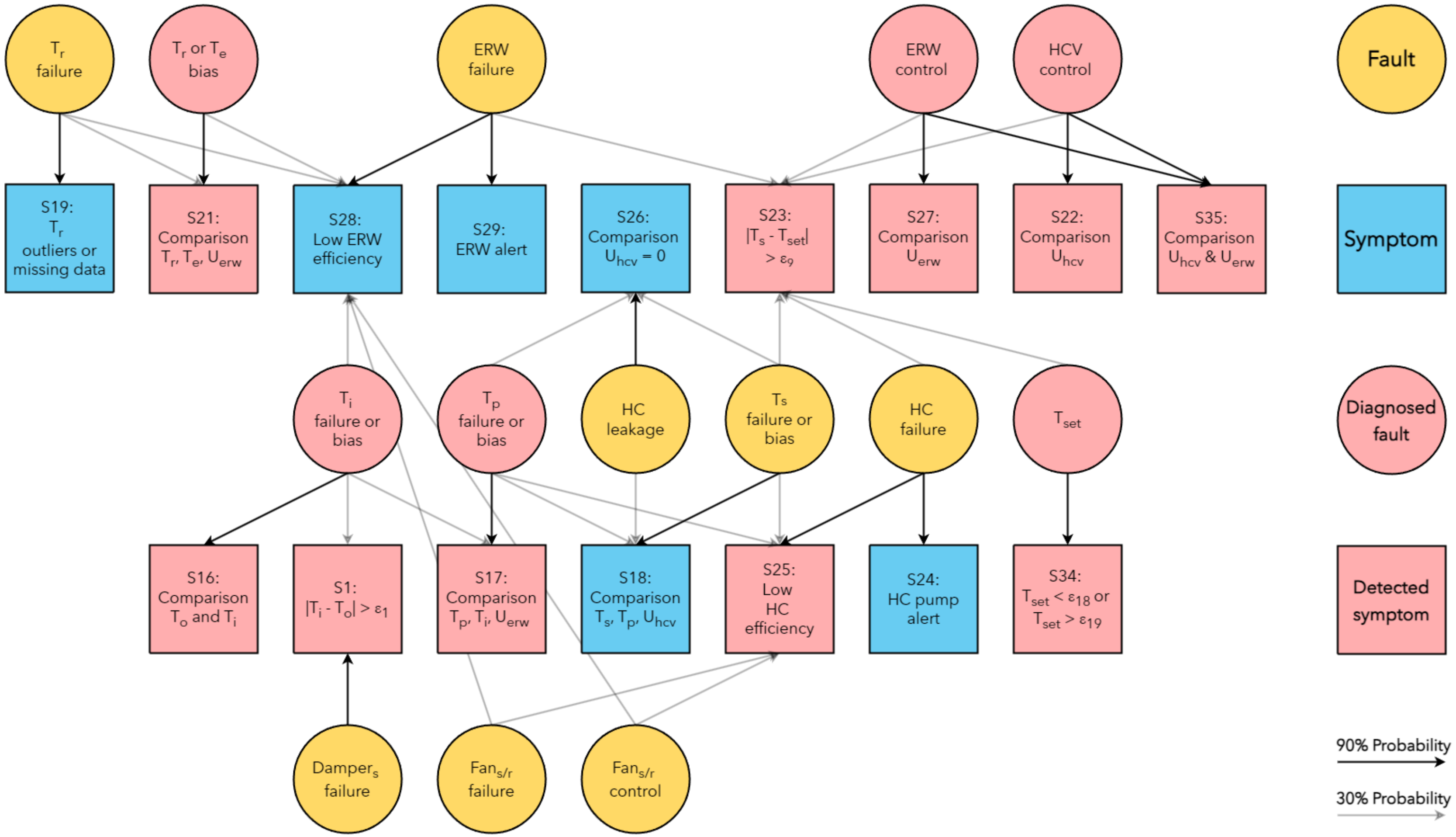
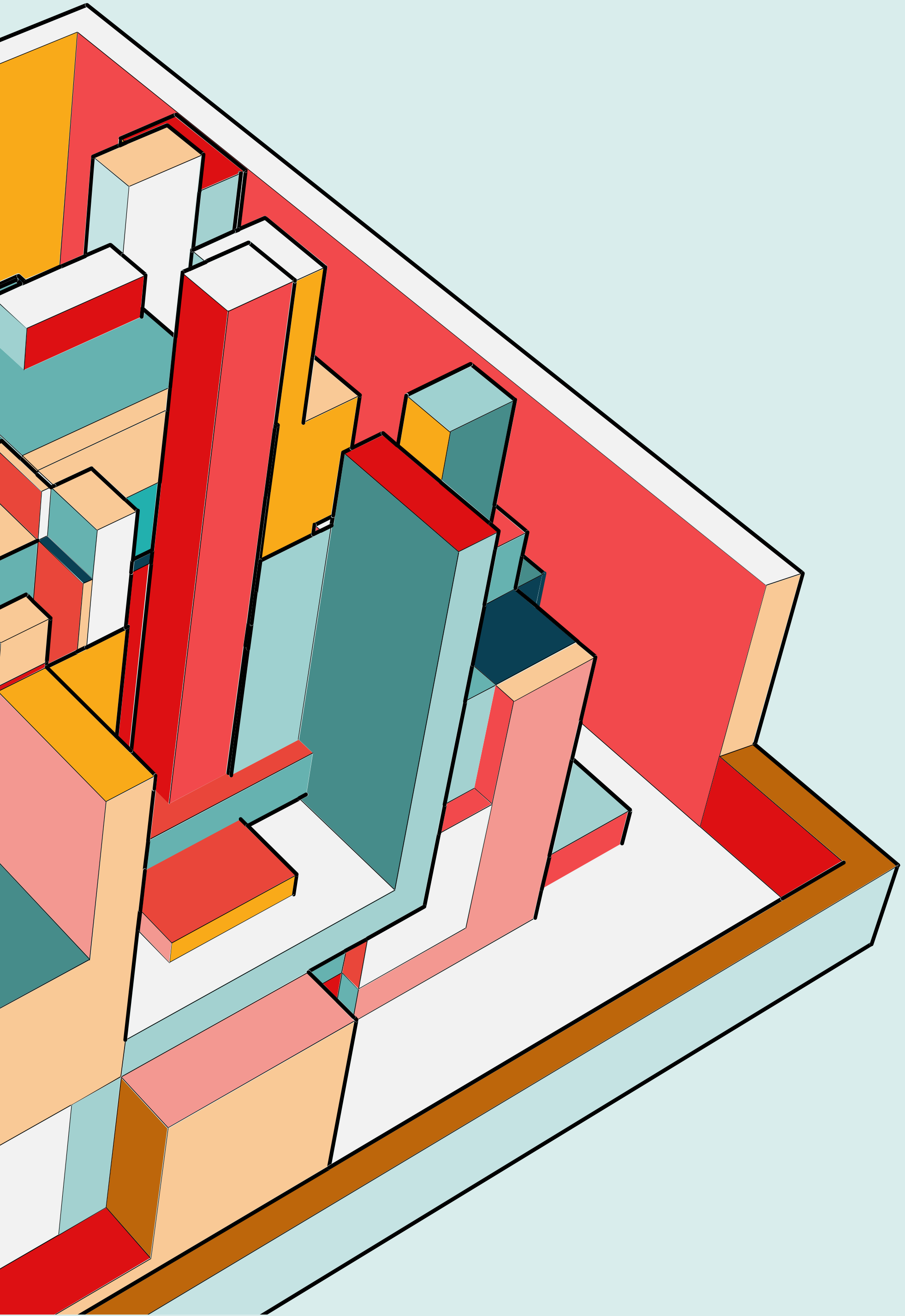


Figure 16: Symptoms and faults diagnosed for real-time data

SUSTAINABILITY IMPLICATIONS

SUSTAINABILITY IMPLICATIONS

- Historical faults with highest impact on energy usage:
  - Lower temperature setpoint **decreases** energy usage (64% of the days considered)
  - Incorrect HCV control fault **increases** energy usage (43% of days considered)
  - Unstable or incorrect ERW control **increases** energy usage (11% of days considered)
- Real-time result related to energy usage:
  - ERW used for cold recovery in addition to heat recovery



CONCLUSION

RESEARCH QUESTION

‘How can Bayesian network-based fault diagnosis accurately find faults for air-handling units in real-time based on expert knowledge?’

CONCLUSION

- The proposed method can reliably diagnose AHU control faults in real-time
- However, diagnosis period of at least one hour is recommended
- Incorrect ERW and HCV control signals frequently diagnosed

LIMITATIONS

- The DBN relies on estimations for parameters and symptom rules
- Missing sensor data impacted historical results
- Transient data may have caused false positive symptoms
- Alert data missing in real-time framework

RECOMMENDATIONS FOR FUTURE RESEARCH

- Expanding the DBN
  - Summer season and outside schedule
  - Efficiency estimations for the coils and fans
  - Frozen sensor symptoms [8]
- Filtering transient data [9]
- Integrating alerts in Kafka framework
- Applying the model to different AHUs

THANK YOU

Lars van Koetsveld van Ankeren MSc

L.vankoetsveldvanankeren@tudelft.nl

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MISSING DATA

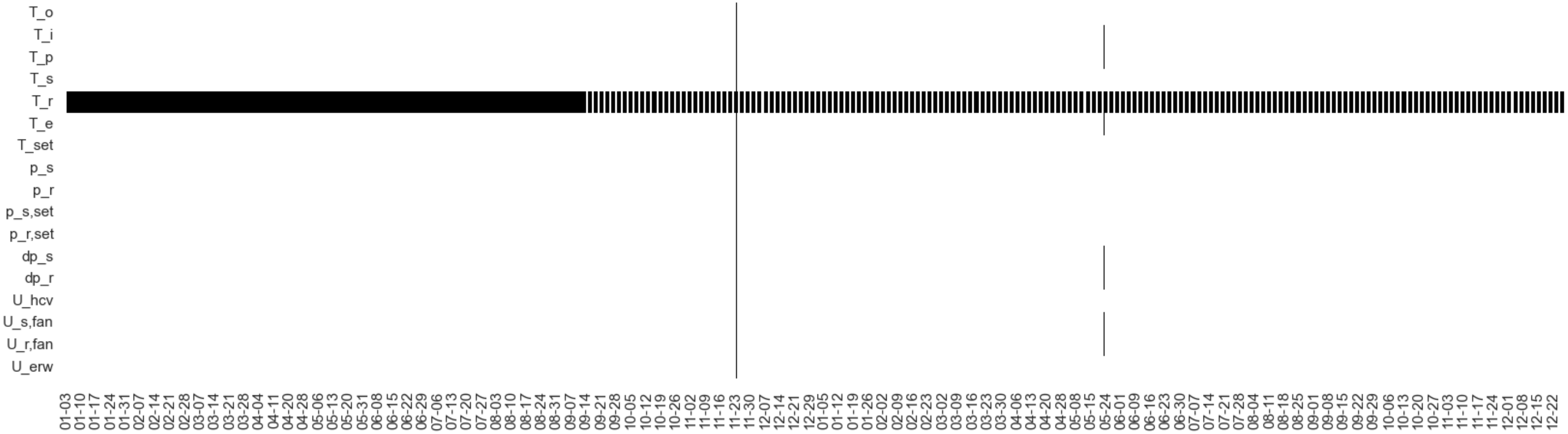


Figure 17: Missing sensor data

DIAGNOSTIC BAYESIAN NETWORK

- Temperature-related faults and symptoms

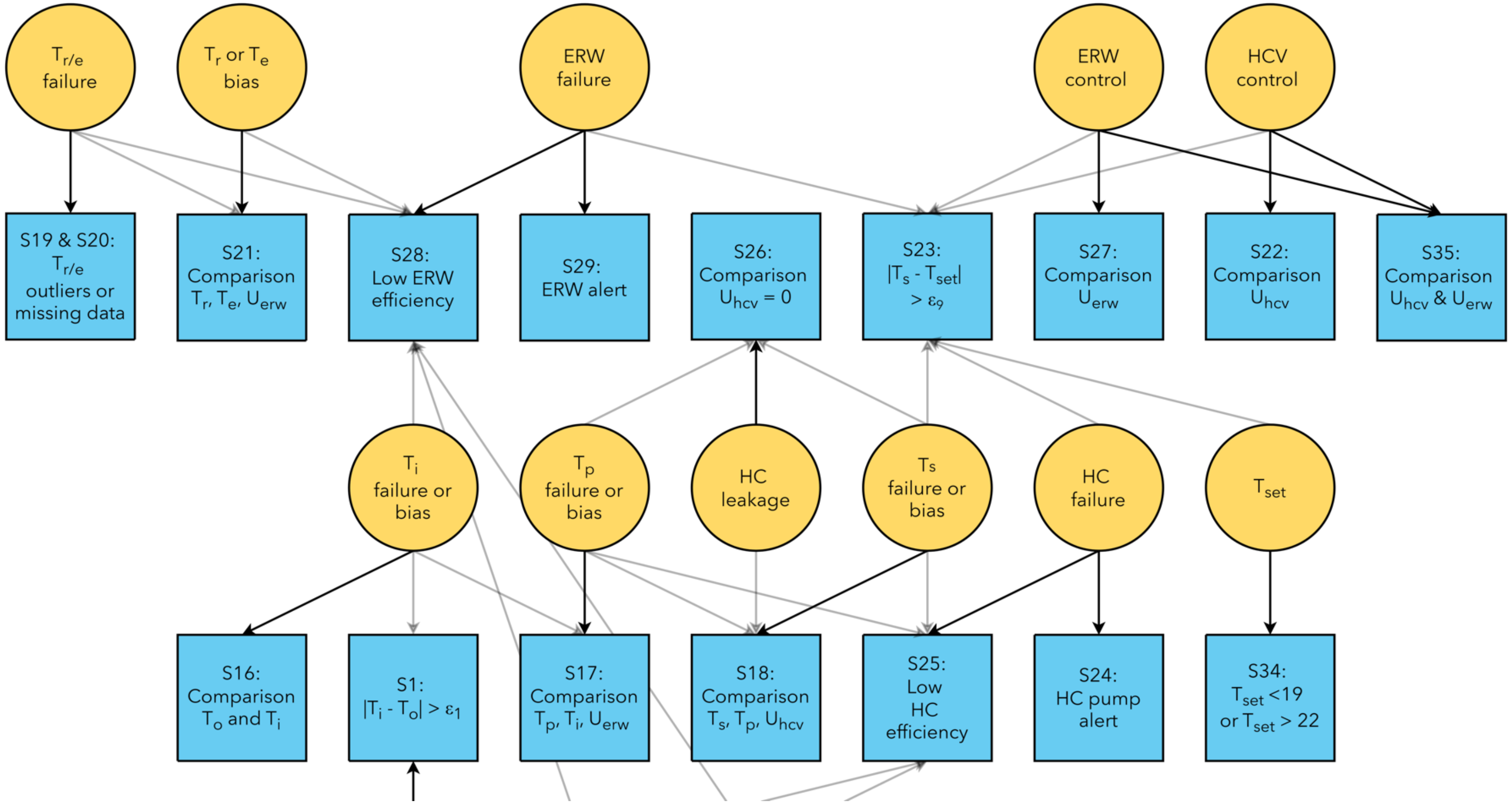


Figure 18: Developed DBN (top)

DIAGNOSTIC BAYESIAN NETWORK

- Pressure-related faults and symptoms

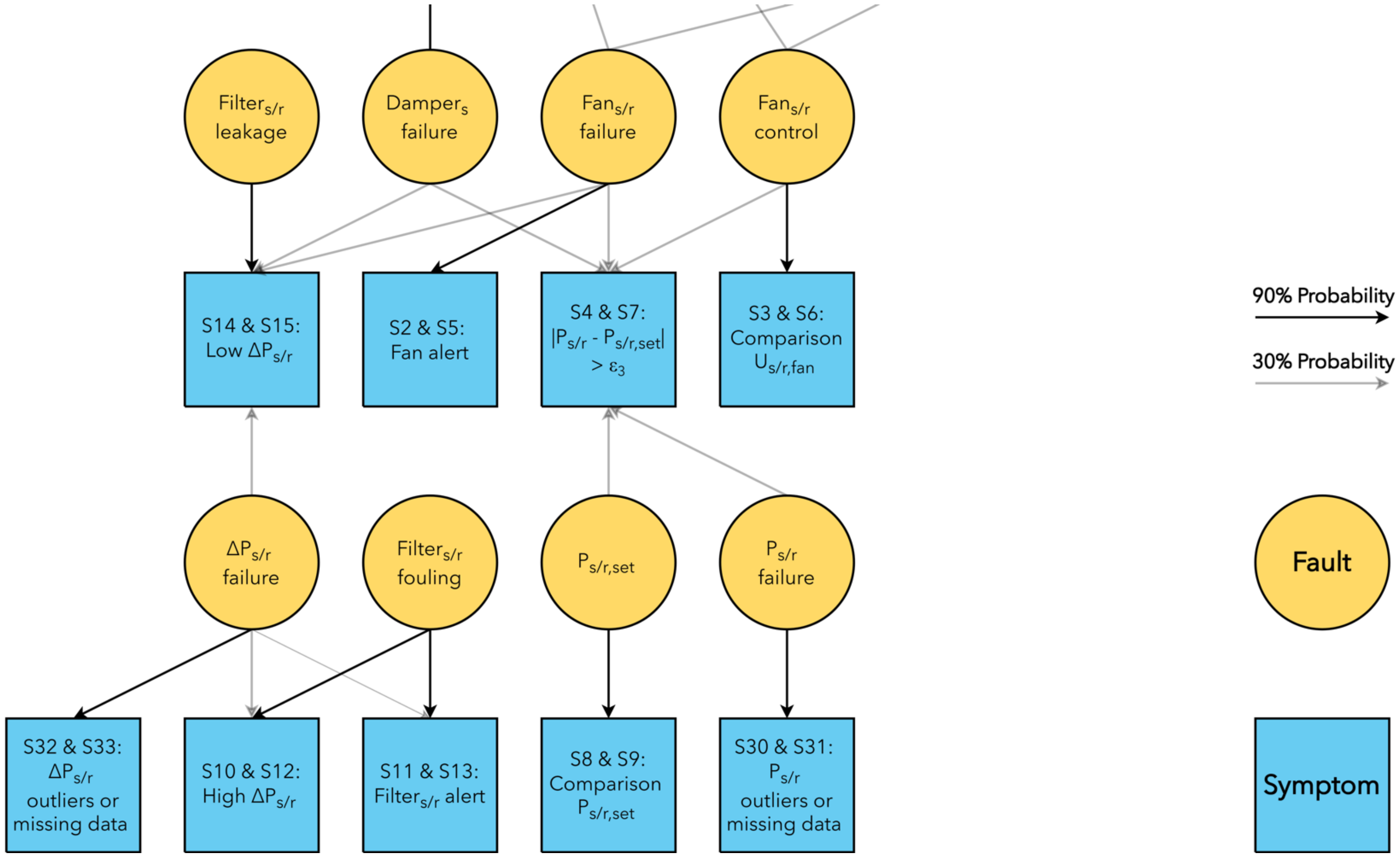


Figure 19: Developed DBN (bottom)

DESCRIPTION OF EXPERIMENTS

- 13 experiments to validate control and sensor faults
- All conducted in March 2024

Date	Fault
03/23/2024	Supply fan control set to 30%
	Supply fan control set to 70%
	ERW control set to 0%
03/24/2024	Supply pressure setpoint set to 235 Pa
	Supply pressure setpoint set to 135 Pa
	Supply pressure sensor set to 130 Pa
03/29/2024	HCV control set to 0%
	HCV control set to 30%
	HCV control set to 100%
03/30/2024	Supply pressure sensor set to 200 Pa
	Temperature setpoint set to 23 °C
	Temperature setpoint set to 17 °C
	Supply temperature sensor set to 17 °C

Figure 20: Conducted experiments

EXPERIMENT RESULTS

- Extra symptom added
- ERW control now also diagnosed correctly

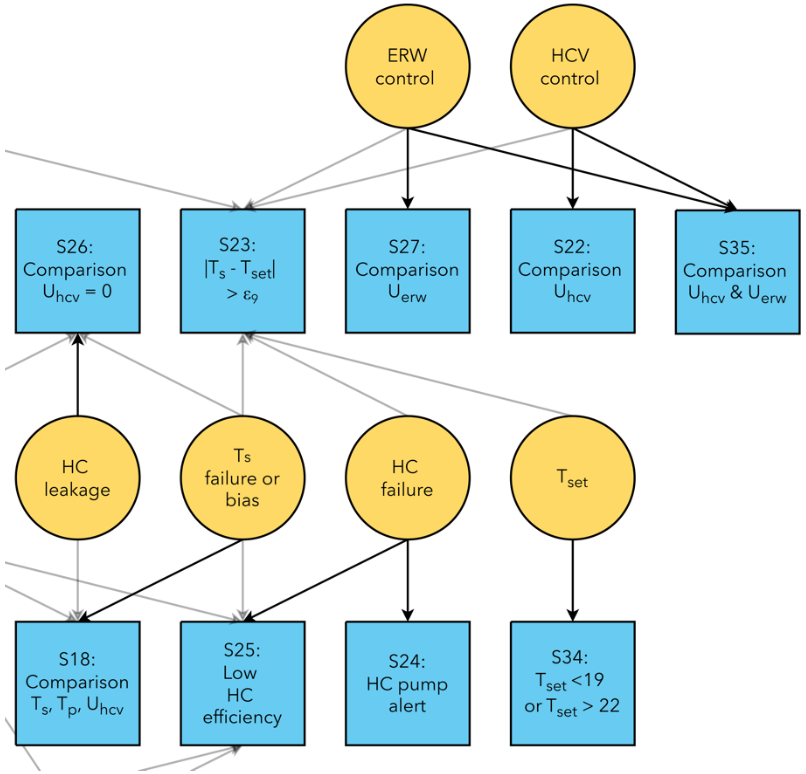
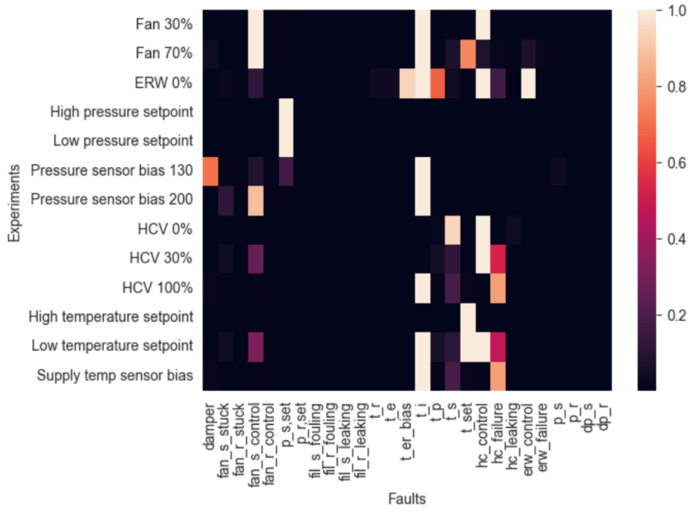
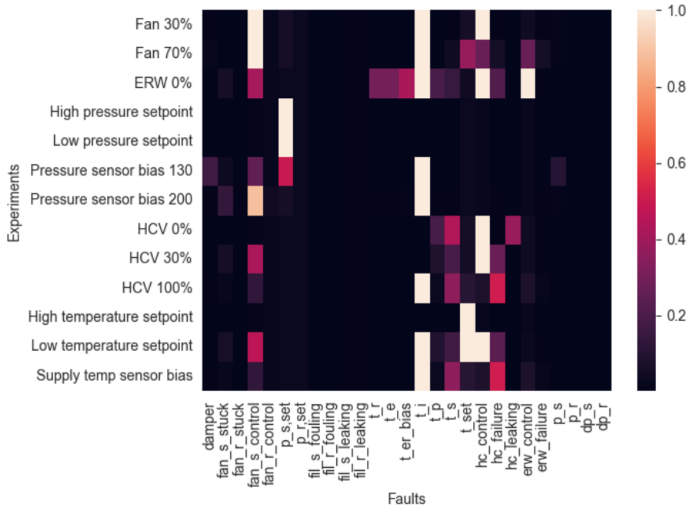


Figure 21: Revised DBN (top-right part)

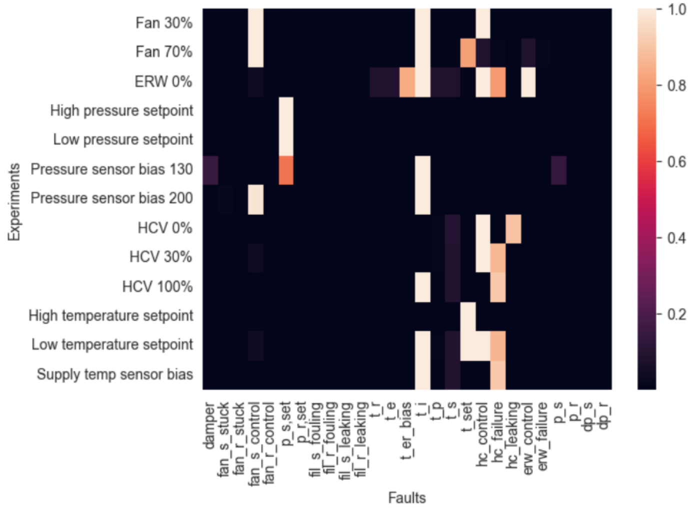
EXPERIMENTAL SENSITIVITY



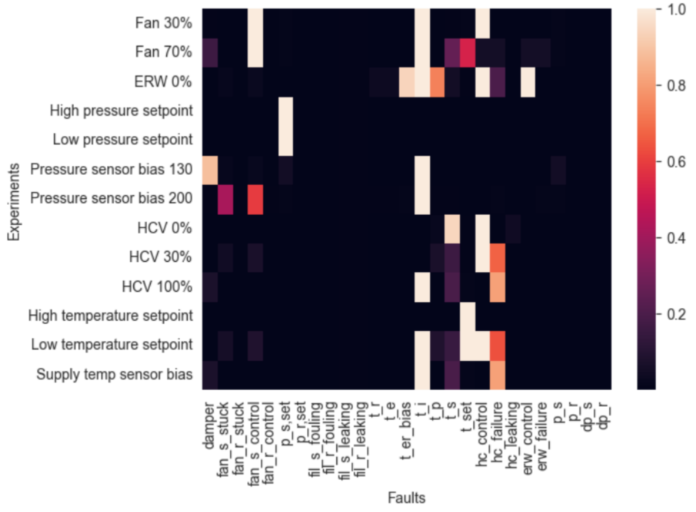
(a) DBN with added symptom S35.



(b) DBN containing only weak links.



(c) DBN containing only strong links.



(d) DBN containing only 5% prior probabilities.

Figure 22: Sensitivity of DBN probabilities for experimental results

HISTORICAL SENSITIVITY

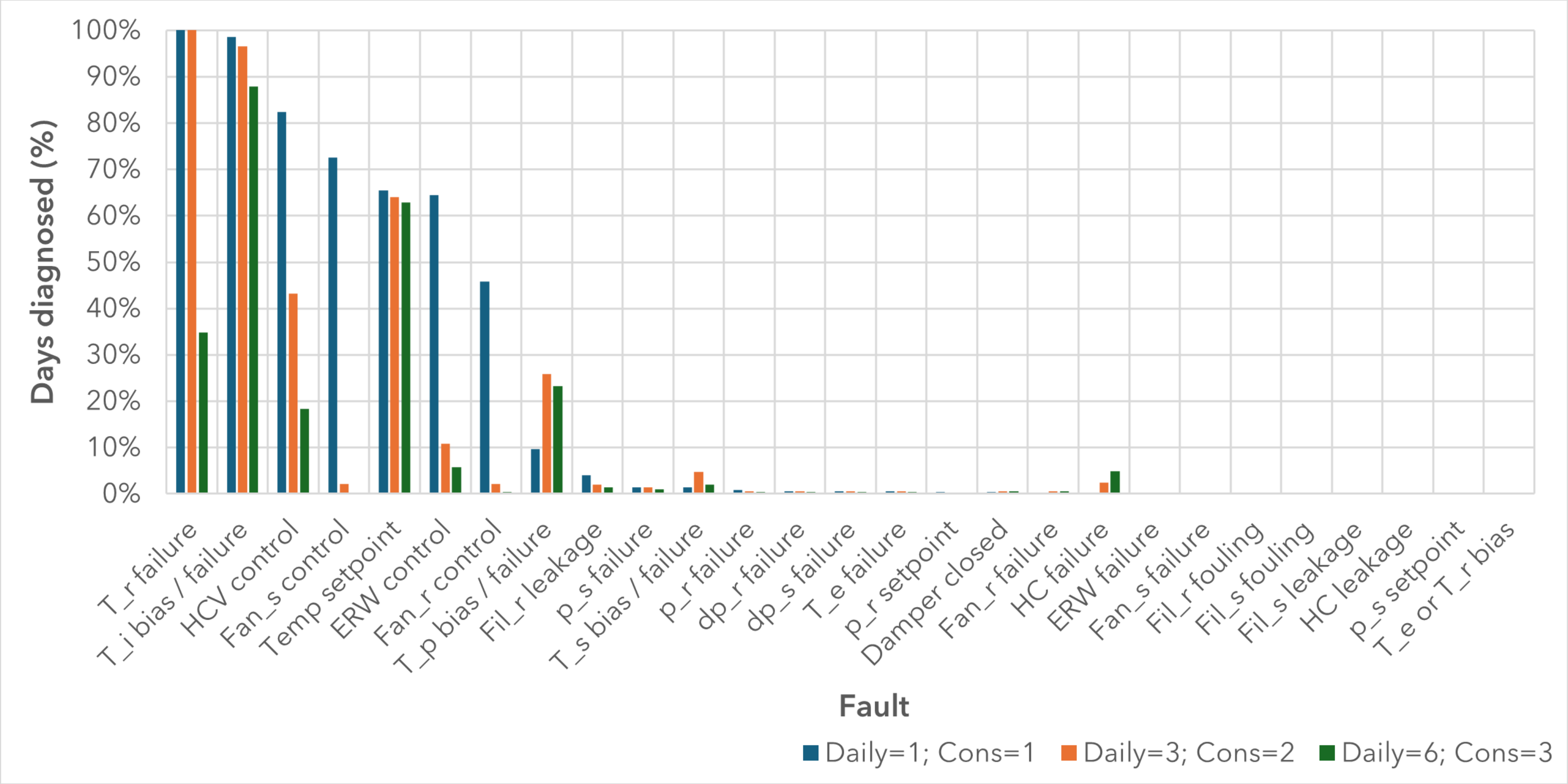


Figure 21: Sensitivity of symptom thresholds for historical results

HISTORICAL SENSITIVITY

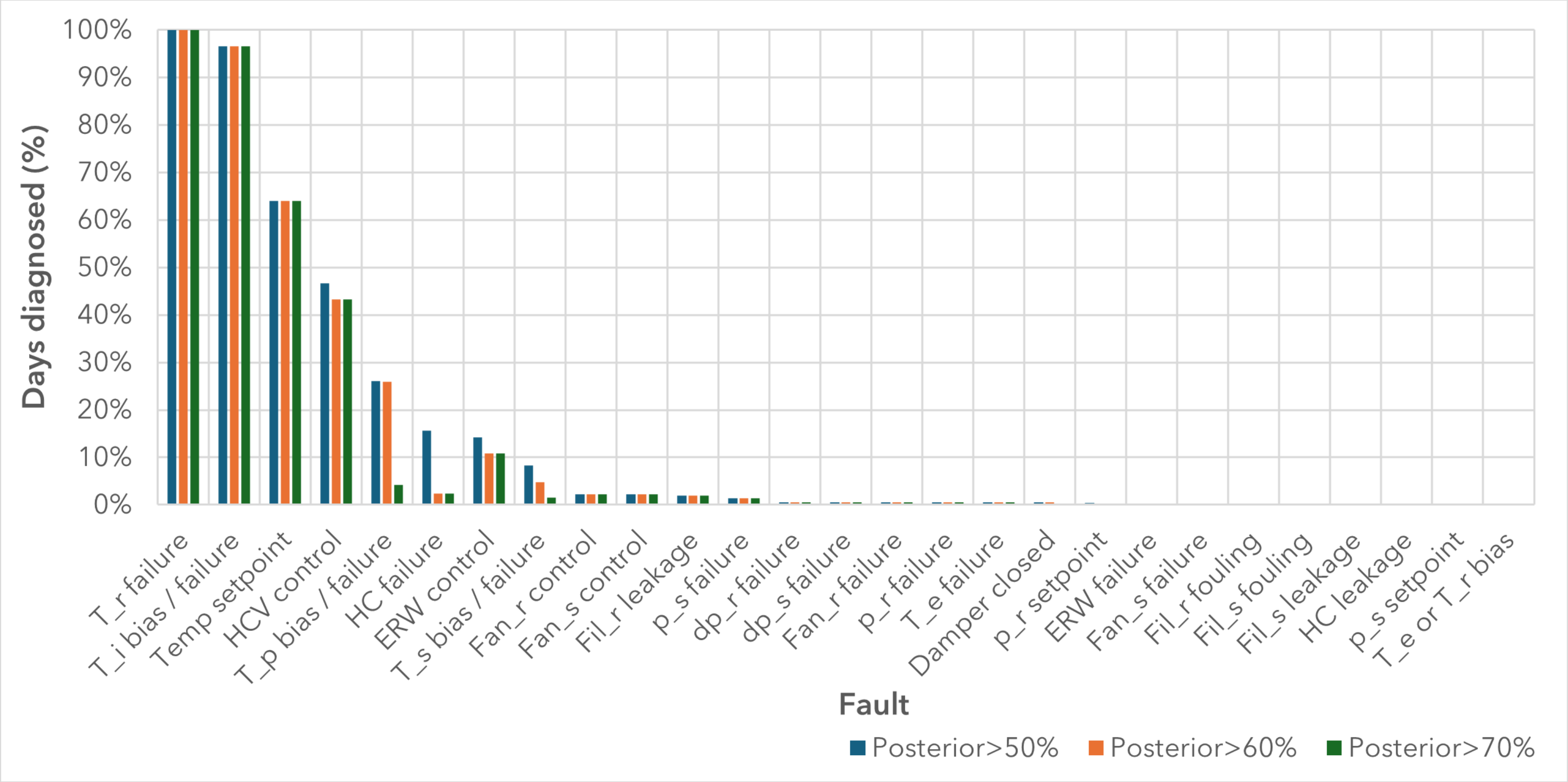


Figure 22: Sensitivity of fault threshold for historical results

DIAGNOSIS RESULTS

- Ten temperature-related symptoms detected
- Biases detected often

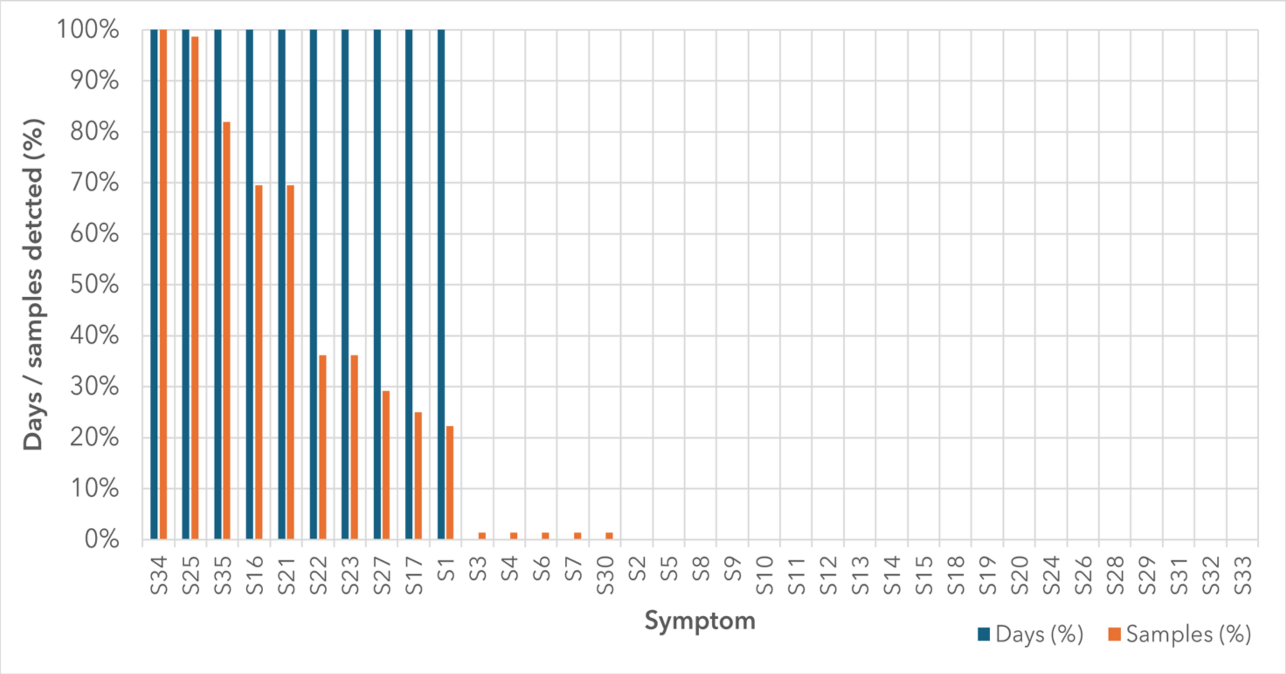


Figure 23: Detected symptoms for real-time data

DIAGNOSIS RESULTS

- Seven temperature-related faults diagnosed
- Mostly control faults

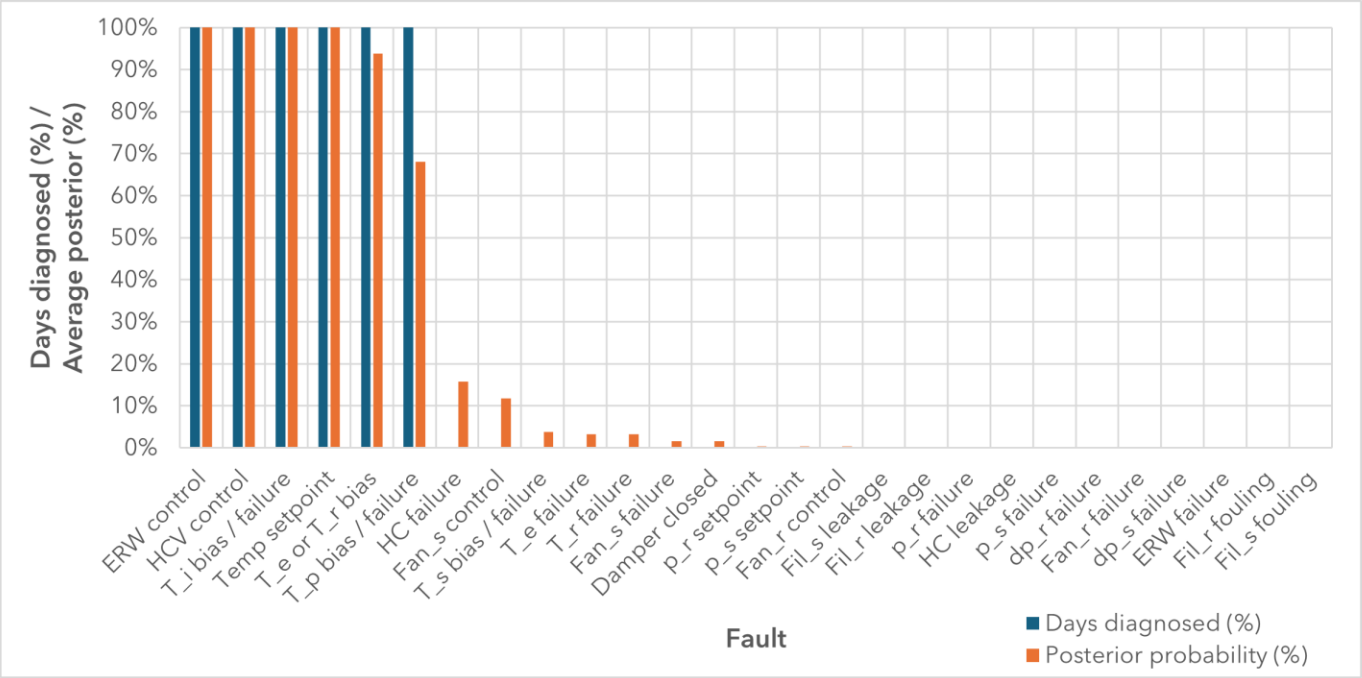


Figure 24: Diagnosed faults for real-time data

DIAGNOSIS RESULTS

- Temperature data provided validation of bias faults
- Bias symptoms are too sensitive

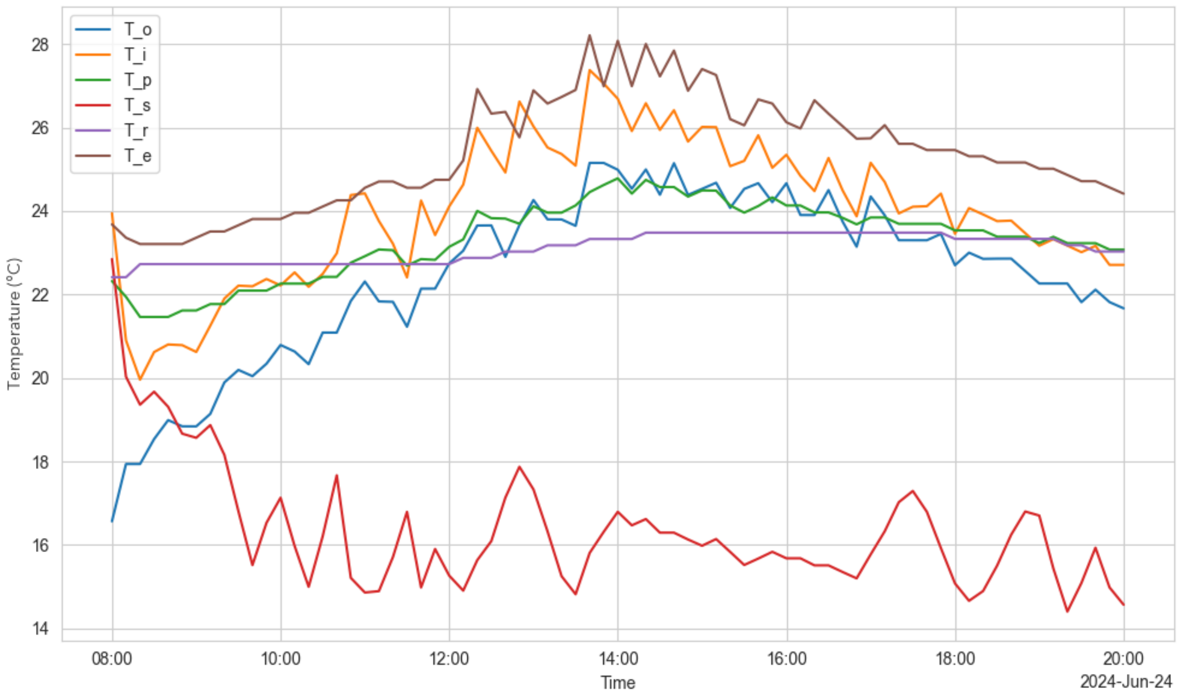


Figure 23: Real-time temperature data

DIAGNOSIS RESULTS

- ERW used for cold recovery
- Different from design document
- HCV opened slightly

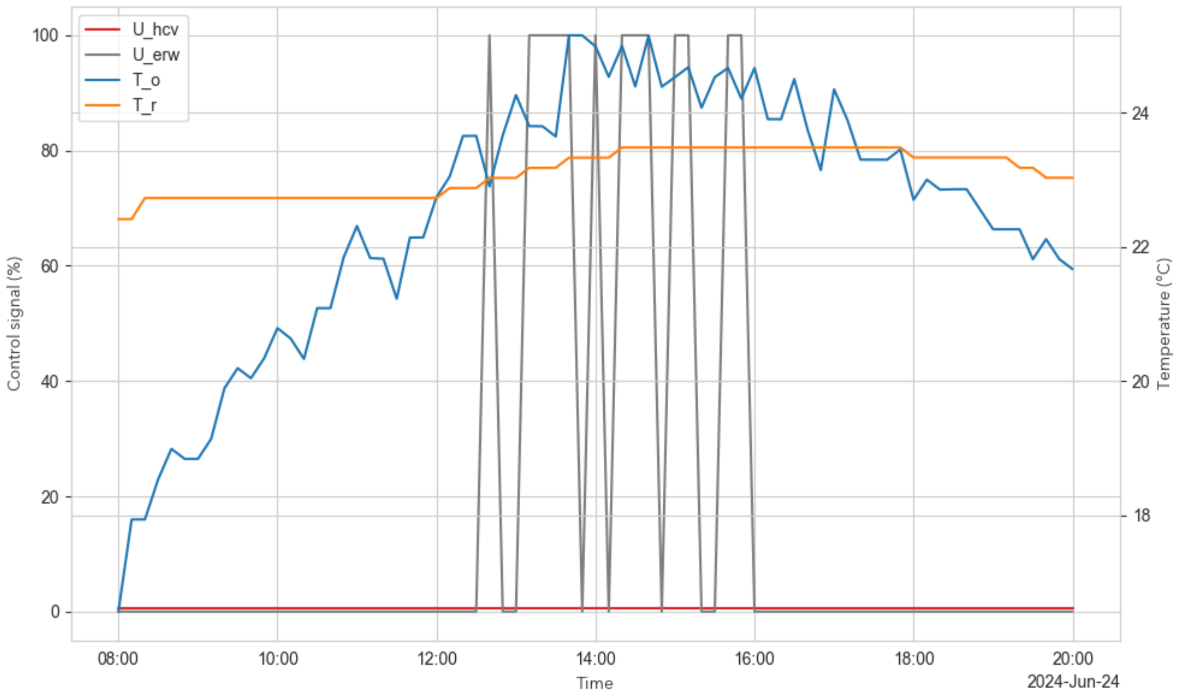


Figure 26: Real-time control data